In [1]:
```
# Importing necessary libraries
import findspark
findspark.init()
findspark.find()

import pyspark

from pyspark.sql import SparkSession
from pyspark import SparkContext, SQLContext
from pyspark.sql.functions import lit

appName = "Project_2"
master = "local"

# Create Configuration object for Spark.
conf = pyspark.SparkConf()\
    .set('spark.driver.host','127.0.0.1')\
    .setAppName(appName)\
    .setMaster(master)

# Create Spark Context with the new configurations rather than relying on the default on
sc = SparkContext.getOrCreate(conf=conf)

# You need to create SQL Context to conduct some database operations like what we will s
sqlContext = SQLContext(sc)

# If you have SQL context, you create the session from the Spark Context
spark = sqlContext.sparkSession.builder.getOrCreate()
```

```
23/11/17 00:45:26 WARN Utils: Your hostname, Kirans-MacBook-Pro.local resolves to a loop
back address: 127.0.0.1; using 192.168.0.11 instead (on interface en0)
23/11/17 00:45:26 WARN Utils: Set SPARK_LOCAL_IP if you need to bind to another address
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLev
el).
23/11/17 00:45:27 WARN NativeCodeLoader: Unable to load native-hadoop library for your p
latform... using builtin-java classes where applicable
23/11/17 00:45:27 WARN Utils: Service 'SparkUI' could not bind on port 4040. Attempting
port 4041.
23/11/17 00:45:27 WARN Utils: Service 'SparkUI' could not bind on port 4041. Attempting
port 4042.
23/11/17 00:45:27 WARN Utils: Service 'SparkUI' could not bind on port 4042. Attempting
port 4043.
23/11/17 00:45:27 WARN Utils: Service 'SparkUI' could not bind on port 4043. Attempting
port 4044.
/Users/kiranprasadjp/aiml/spark-3.5.0-bin-hadoop3/python/pyspark/sql/context.py:113: Fut
ureWarning: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
```

In [2]:
```
# Load data from csv to a dataframe on a local machine.
# header=False means the first row is not a header
# sep=',' means the column are seperated using ','


df_train = spark.read.csv("train70_reduced.csv",header=True, inferSchema= True)
df_test = spark.read.csv("test30_reduced.csv",header=True, inferSchema= True)
df_train = df_train.withColumn("dataset", lit("train"))
df_test = df_test.withColumn("dataset", lit("test"))
df = df_train.union(df_test)
```

In [3]:
```
db_properties={}
db_properties['username']="postgres"
db_properties['password']="Natkanvij@22"
```

```python
db_properties['url']= "jdbc:postgresql://localhost:5432/postgres"

# I have kept the table name as intrusion2
db_properties['table']="MQTT"
db_properties['driver']="org.postgresql.Driver"

df.write.format("jdbc")\
.mode("overwrite")\
.option("url", db_properties['url'])\
.option("dbtable", db_properties['table'])\
.option("user", db_properties['username'])\
.option("password", db_properties['password'])\
.option("Driver", db_properties['driver'])\
.save()
```

In [4]:
```python
df_read = sqlContext.read.format("jdbc")\
    .option("url", db_properties['url'])\
    .option("dbtable", db_properties['table'])\
    .option("user", db_properties['username'])\
    .option("password", db_properties['password'])\
    .option("Driver", db_properties['driver'])\
    .load()

df_read.show(1, vertical=True)
df_read.printSchema()
```

```
-RECORD 0----------------------------------
 tcp.flags                    | 0x00000018
 tcp.time_delta               | 0.998867
 tcp.len                      | 10
 mqtt.conack.flags            | 0
 mqtt.conack.flags.reserved   | 0.0
 mqtt.conack.flags.sp         | 0.0
 mqtt.conack.val              | 0.0
 mqtt.conflag.cleansess       | 0.0
 mqtt.conflag.passwd          | 0.0
 mqtt.conflag.qos             | 0.0
 mqtt.conflag.reserved        | 0.0
 mqtt.conflag.retain          | 0.0
 mqtt.conflag.uname           | 0.0
 mqtt.conflag.willflag        | 0.0
 mqtt.conflags                | 0
 mqtt.dupflag                 | 0.0
 mqtt.hdrflags                | 0x00000030
 mqtt.kalive                  | 0.0
 mqtt.len                     | 8.0
 mqtt.msg                     | 32
 mqtt.msgid                   | 0.0
 mqtt.msgtype                 | 3.0
 mqtt.proto_len               | 0.0
 mqtt.protoname               | 0
 mqtt.qos                     | 0.0
 mqtt.retain                  | 0.0
 mqtt.sub.qos                 | 0.0
 mqtt.suback.qos              | 0.0
 mqtt.ver                     | 0.0
 mqtt.willmsg                 | 0.0
 mqtt.willmsg_len             | 0.0
 mqtt.willtopic               | 0.0
 mqtt.willtopic_len           | 0.0
 target                       | legitimate
 dataset                      | train
only showing top 1 row

root
```

```
 |-- tcp.flags: string (nullable = true)
 |-- tcp.time_delta: double (nullable = true)
 |-- tcp.len: integer (nullable = true)
 |-- mqtt.conack.flags: string (nullable = true)
 |-- mqtt.conack.flags.reserved: double (nullable = true)
 |-- mqtt.conack.flags.sp: double (nullable = true)
 |-- mqtt.conack.val: double (nullable = true)
 |-- mqtt.conflag.cleansess: double (nullable = true)
 |-- mqtt.conflag.passwd: double (nullable = true)
 |-- mqtt.conflag.qos: double (nullable = true)
 |-- mqtt.conflag.reserved: double (nullable = true)
 |-- mqtt.conflag.retain: double (nullable = true)
 |-- mqtt.conflag.uname: double (nullable = true)
 |-- mqtt.conflag.willflag: double (nullable = true)
 |-- mqtt.conflags: string (nullable = true)
 |-- mqtt.dupflag: double (nullable = true)
 |-- mqtt.hdrflags: string (nullable = true)
 |-- mqtt.kalive: double (nullable = true)
 |-- mqtt.len: double (nullable = true)
 |-- mqtt.msg: string (nullable = true)
 |-- mqtt.msgid: double (nullable = true)
 |-- mqtt.msgtype: double (nullable = true)
 |-- mqtt.proto_len: double (nullable = true)
 |-- mqtt.protoname: string (nullable = true)
 |-- mqtt.qos: double (nullable = true)
 |-- mqtt.retain: double (nullable = true)
 |-- mqtt.sub.qos: double (nullable = true)
 |-- mqtt.suback.qos: double (nullable = true)
 |-- mqtt.ver: double (nullable = true)
 |-- mqtt.willmsg: double (nullable = true)
 |-- mqtt.willmsg_len: double (nullable = true)
 |-- mqtt.willtopic: double (nullable = true)
 |-- mqtt.willtopic_len: double (nullable = true)
 |-- target: string (nullable = true)
 |-- dataset: string (nullable = true)
```

Renaming coloumns with . to _

In [5]:

```python
from pyspark.sql.functions import col

def replace_dot_with_underscore(data_df):
    # Replace '.' with '_' in column names
    for col_name in data_df.columns:
        new_col_name = col_name.replace('.', '_')
        data_df = data_df.withColumnRenamed(col_name, new_col_name)
    return data_df
renamed_columns_df = replace_dot_with_underscore(df_read)
```

In [6]:

```python
renamed_columns_df.printSchema()
```

```
root
 |-- tcp_flags: string (nullable = true)
 |-- tcp_time_delta: double (nullable = true)
 |-- tcp_len: integer (nullable = true)
 |-- mqtt_conack_flags: string (nullable = true)
 |-- mqtt_conack_flags_reserved: double (nullable = true)
 |-- mqtt_conack_flags_sp: double (nullable = true)
 |-- mqtt_conack_val: double (nullable = true)
 |-- mqtt_conflag_cleansess: double (nullable = true)
 |-- mqtt_conflag_passwd: double (nullable = true)
 |-- mqtt_conflag_qos: double (nullable = true)
 |-- mqtt_conflag_reserved: double (nullable = true)
 |-- mqtt_conflag_retain: double (nullable = true)
 |-- mqtt_conflag_uname: double (nullable = true)
```

```
 |-- mqtt_conflag_willflag: double (nullable = true)
 |-- mqtt_conflags: string (nullable = true)
 |-- mqtt_dupflag: double (nullable = true)
 |-- mqtt_hdrflags: string (nullable = true)
 |-- mqtt_kalive: double (nullable = true)
 |-- mqtt_len: double (nullable = true)
 |-- mqtt_msg: string (nullable = true)
 |-- mqtt_msgid: double (nullable = true)
 |-- mqtt_msgtype: double (nullable = true)
 |-- mqtt_proto_len: double (nullable = true)
 |-- mqtt_protoname: string (nullable = true)
 |-- mqtt_qos: double (nullable = true)
 |-- mqtt_retain: double (nullable = true)
 |-- mqtt_sub_qos: double (nullable = true)
 |-- mqtt_suback_qos: double (nullable = true)
 |-- mqtt_ver: double (nullable = true)
 |-- mqtt_willmsg: double (nullable = true)
 |-- mqtt_willmsg_len: double (nullable = true)
 |-- mqtt_willtopic: double (nullable = true)
 |-- mqtt_willtopic_len: double (nullable = true)
 |-- target: string (nullable = true)
 |-- dataset: string (nullable = true)
```

In [7]:

```
from pyspark.sql.functions import avg


# Filter the DataFrame to select only rows where 'dataset' is 'train'
train_df = renamed_columns_df.filter(renamed_columns_df['dataset'] == 'train')

# Calculate the average of the 'len' column for the 'train' dataset
average_length = train_df.agg(avg('mqtt_len')).collect()[0][0]

# Print the average length
print("Average length for 'train' dataset:", average_length)
```

```
Average length for 'train' dataset: 31.435725201384873
```

In [8]:

```
average_lengths = renamed_columns_df.groupBy('target').agg(avg('tcp_len').alias('average
df = renamed_columns_df
average_lengths.show()
```

```
+----------+------------------+
|    target|average_tcp_length|
+----------+------------------+
|   slowite|3.9993479678330797|
|bruteforce|3.9871043376318873|
|     flood|13313.415986949429|
| malformed| 20.97491761259612|
|       dos|312.65759830457716|
|legitimate| 7.776101001432345|
+----------+------------------+
```

In [9]:

```
from pyspark.sql.functions import dense_rank, desc
from pyspark.sql.window import Window


def get_X_most_frequent_tcp_flags(x):
    distinct_flags = df.select('tcp_flags').distinct().count()
    if x > distinct_flags:
        print(f"There are only {distinct_flags} distinct TCP flags in this dataset. Show
        x = distinct_flags
    window_spec = Window.partitionBy().orderBy(desc('count'))
    ranked_df = df.groupBy('tcp_flags').count().orderBy(desc('count')).withColumn("dense
```

```
    result = ranked_df.filter(col("dense_rank") <= x)
    result.show()
```

In [10]:
```
get_X_most_frequent_tcp_flags(4)
```

```
+----------+------+----------+
| tcp_flags| count|dense_rank|
+----------+------+----------+
|0x00000018|183076|         1|
|0x00000010|134547|         2|
|0x00000011|  4198|         3|
|0x00000002|  3372|         4|
|0x00000012|  3372|         4|
+----------+------+----------+
```

In [11]:
```
from pyspark.sql.functions import when

renamed_columns_df = renamed_columns_df.withColumn("target", when(renamed_columns_df["ta
renamed_columns_df = renamed_columns_df.withColumn("target", when(renamed_columns_df["ta
```

In [12]:
```
unique_target_types = renamed_columns_df.select('target').distinct()

# Collect the unique values and convert them to a list
unique_target_types_list = [row.target for row in unique_target_types.collect()]

# Print the unique protocol types
print("Unique Targets we have from the dataset:")
for target in unique_target_types_list:
    print(target)
```

```
Unique Targets we have from the dataset:
slowite
flood
brute-force
malformed
denial-of-service
legitimate
```

In [13]:
```
from confluent_kafka import Producer
import socket
#Initialize Your Parameters here - Keep the variable values as is for the ones you can't
KAFKA_CONFIG = {
    "bootstrap.servers":"pkc-lzvrd.us-west4.gcp.confluent.cloud:9092",
    "security.protocol":"SASL_SSL",
    "sasl.mechanisms":"PLAIN",
    "sasl.username":"LKGBAJ3FAQY7XT3O",
    "sasl.password":"FdsLkF9Cec8qkthIz9EAny8whhp9dZ9Wa0/YuBQZa2JjEsF/61KnaGkkpK7VW9fk",
    "session.timeout.ms":"45000",
    "group.id":"python-group-1",
    'auto.offset.reset': 'smallest',
    'client.id': socket.gethostname()
}

# Update your topic name
topic_name = "topic_0"
producer = Producer(KAFKA_CONFIG)
```

In [14]:
```
import feedparser
import time

# We are searching for Analytics in the news
feed_url = "https://news.google.com/rss/search?q=popular+cyber+attacks"
```

```python
def extract_news_feed(feed_url, runtime_minutes):
    feed = feedparser.parse(feed_url)
    articles = []
    extracted_articles = set()
    start_time = time.time()
    end_time = start_time + (runtime_minutes * 60)  # Convert minutes to seconds
    while time.time() < end_time:
        for entry in feed.entries:
            link = entry.link
            title = entry.title.encode('ascii', 'ignore').decode()
            unique_id = f'{link}-{title}'
            if unique_id in extracted_articles:
                continue
            extracted_articles.add(unique_id)
            article_data = {"title": title, "link": link}
            if article_data is not None:
                producer.produce(topic_name, key=article_data["title"], value=article_da
        producer.flush()

extract_news_feed(feed_url, runtime_minutes=5)
```

In [15]:
```python
from confluent_kafka import Consumer
from pyspark.sql.types import *
import string


# Clean the punctation by making a translation table that maps punctations to empty stri
translator = str.maketrans("", "", string.punctuation.replace('-', ''))


emp_RDD = spark.sparkContext.emptyRDD()
# Defining the schema of the DataFrame
columns = StructType([StructField('key', StringType(), False),
                      StructField('value', StringType(), False)])

# Creating an empty DataFrame
df = spark.createDataFrame(data=emp_RDD,
                                   schema=columns)

# Printing the DataFrame with no data
df.show()

consumer = Consumer(KAFKA_CONFIG)
consumer.subscribe([topic_name])

try:
    i = 0
    while i < 5:
        msg = consumer.poll(timeout=1.0)
        if msg is None:
            i = i + 1
            print("Waiting...")
            continue
        if msg is not None:
            key = msg.key().decode('utf-8').lower().translate(translator)
            #print(key)
            cleaned_key = " ".join(key.split())
            value = msg.value().decode('utf-8')
            added_row = [[cleaned_key,value]]
            added_df = spark.createDataFrame(added_row, columns)
            df = df.union(added_df)

except KeyboardInterrupt:
    pass
finally:
```

```
    consumer.close()
    df.show()
```

```
+---+-----+
|key|value|
+---+-----+
+---+-----+

Waiting...
Waiting...
Waiting...
Waiting...
Waiting...
+---+-----+
|key|value|
+---+-----+
+---+-----+
```

In [ ]:

```

```

In [16]:

```
from pyspark.sql.functions import *
# import nltk
# nltk.download('stopwords')

# stop_words = nltk.corpus.stopwords.words('english')
streamed_data = df.withColumn('word', explode(split(col('key'), ' '))) \
                .filter(col('word').isin(unique_target_types_list)) \
                .groupBy('word') \
                .count() \
                .sort('count', ascending=False)



streamed_data.show()
```

```
+----+-----+
|word|count|
+----+-----+
+----+-----+
```

renaming the target values to the original type

In [83]:

```
from pyspark.sql.functions import when

renamed_columns_df = renamed_columns_df.withColumn("target", when(renamed_columns_df["ta
renamed_columns_df = renamed_columns_df.withColumn("target", when(renamed_columns_df["ta
```

Task- III Machine Learning Modeling

Feature Engineering

Check for Null and NA values in the coloumns

In [ ]:

```

```

In [84]:

```
from pyspark.sql.functions import *

null_df = renamed_columns_df.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c)
                        for c in renamed_columns_df.columns])

null_df.show(truncate=False, vertical=True)
```

```
-RECORD 0-------------------------
 tcp_flags                    | 0
 tcp_time_delta               | 0
 tcp_len                      | 0
 mqtt_conack_flags            | 0
 mqtt_conack_flags_reserved   | 0
 mqtt_conack_flags_sp         | 0
 mqtt_conack_val              | 0
 mqtt_conflag_cleansess       | 0
 mqtt_conflag_passwd          | 0
 mqtt_conflag_qos             | 0
 mqtt_conflag_reserved        | 0
 mqtt_conflag_retain          | 0
 mqtt_conflag_uname           | 0
 mqtt_conflag_willflag        | 0
 mqtt_conflags                | 0
 mqtt_dupflag                 | 0
 mqtt_hdrflags                | 0
 mqtt_kalive                  | 0
 mqtt_len                     | 0
 mqtt_msg                     | 0
 mqtt_msgid                   | 0
 mqtt_msgtype                 | 0
 mqtt_proto_len               | 0
 mqtt_protoname               | 0
 mqtt_qos                     | 0
 mqtt_retain                  | 0
 mqtt_sub_qos                 | 0
 mqtt_suback_qos              | 0
 mqtt_ver                     | 0
 mqtt_willmsg                 | 0
 mqtt_willmsg_len             | 0
 mqtt_willtopic               | 0
 mqtt_willtopic_len           | 0
 target                       | 0
 dataset                      | 0
```

There are no null/NA values in the coloumns of our dataset. Thus, we do not need to do imputation for null/Na values.

Checking duplicate rows

In [85]:

```
row_count = renamed_columns_df.count()
print(f"Current number of rows:{row_count}")

df = renamed_columns_df.dropDuplicates()
row_count = df.count()
print(f"After eliminating duplicates, current number of rows:{row_count}")
```

```
Current number of rows:330936
After eliminating duplicates, current number of rows:131711
```

Classifying our columns

To classify our columns lets first check the unique values in the coloumns.

In [86]:

```
for column in renamed_columns_df.columns:
    unique_values = df.select(column).distinct()
    print(f"Column: {column}")
    unique_values.show(truncate=False)
    print("\n")
```

```
Column: tcp_flags
```

```
+----------+
|tcp_flags |
+----------+
|0x00000004|
|0x00000010|
|0x00000019|
|0x00000002|
|0x00000012|
|0x00000014|
|0x00000018|
|0x00000011|
+----------+


Column: tcp_time_delta
+--------------+
|tcp_time_delta|
+--------------+
|0.00457       |
|8.77E-4       |
|0.999942      |
|1.000047      |
|0.00195       |
|1.00005       |
|7.18E-4       |
|7.5E-4        |
|0.003369      |
|0.498969      |
|0.001045      |
|1.001015      |
|0.498877      |
|0.003699      |
|3.71E-4       |
|0.049345      |
|0.001243      |
|0.003333      |
|0.018394      |
|0.500367      |
+--------------+
only showing top 20 rows


Column: tcp_len
+-------+
|tcp_len|
+-------+
|148    |
|496    |
|1342   |
|833    |
|1460   |
|858    |
|1025   |
|540    |
|1395   |
|392    |
|31     |
|516    |
|1352   |
|85     |
|580    |
|137    |
|65     |
|883    |
```

```
|879    |
|1223   |
+-------+
only showing top 20 rows


Column: mqtt_conack_flags
+-----------------+
|mqtt_conack_flags|
+-----------------+
|0                |
|0x00000000       |
+-----------------+


Column: mqtt_conack_flags_reserved
+--------------------------+
|mqtt_conack_flags_reserved|
+--------------------------+
|0.0                       |
+--------------------------+


Column: mqtt_conack_flags_sp
+--------------------+
|mqtt_conack_flags_sp|
+--------------------+
|0.0                 |
+--------------------+


Column: mqtt_conack_val
+---------------+
|mqtt_conack_val|
+---------------+
|0.0            |
|5.0            |
+---------------+


Column: mqtt_conflag_cleansess
+----------------------+
|mqtt_conflag_cleansess|
+----------------------+
|0.0                   |
|1.0                   |
+----------------------+


Column: mqtt_conflag_passwd
+-------------------+
|mqtt_conflag_passwd|
+-------------------+
|0.0                |
|1.0                |
+-------------------+


Column: mqtt_conflag_qos
```

```
+-----------------+
|mqtt_conflag_qos|
+-----------------+
|0.0             |
+-----------------+
```

```
Column: mqtt_conflag_reserved
+----------------------+
|mqtt_conflag_reserved|
+----------------------+
|0.0                  |
+----------------------+
```

```
Column: mqtt_conflag_retain
+--------------------+
|mqtt_conflag_retain|
+--------------------+
|0.0                |
+--------------------+
```

```
Column: mqtt_conflag_uname
+-------------------+
|mqtt_conflag_uname|
+-------------------+
|0.0               |
|1.0               |
+-------------------+
```

```
Column: mqtt_conflag_willflag
+----------------------+
|mqtt_conflag_willflag|
+----------------------+
|0.0                  |
+----------------------+
```

```
Column: mqtt_conflags
+--------------+
|mqtt_conflags|
+--------------+
|0            |
|0x00000082   |
|0x00000002   |
|0x000000c2   |
+--------------+
```

```
Column: mqtt_dupflag
+-------------+
|mqtt_dupflag|
+-------------+
|0.0         |
|1.0         |
+-------------+
```

```
Column: mqtt_hdrflags
+-------------+
|mqtt_hdrflags|
+-------------+
|0x00000031   |
|0x00000090   |
|0            |
|0x000000d0   |
|0x00000010   |
|0x00000082   |
|0x00000030   |
|0x00000040   |
|0x000000e0   |
|0x00000020   |
|0x0000003a   |
|0x00000032   |
|0x00000050   |
|0x000000c0   |
+-------------+
```

```
Column: mqtt_kalive
+-----------+
|mqtt_kalive|
+-----------+
|0.0        |
|234.0      |
|1.0        |
|60.0       |
|65535.0    |
|3.0        |
|2.0        |
+-----------+
```

```
Column: mqtt_len
+--------+
|mqtt_len|
+--------+
|692.0   |
|170.0   |
|184.0   |
|169.0   |
|160.0   |
|8.0     |
|168.0   |
|0.0     |
|7.0     |
|154.0   |
|180.0   |
|181.0   |
|49.0    |
|155.0   |
|167.0   |
|29.0    |
|182.0   |
|47.0    |
|42.0    |
|44.0    |
+--------+
only showing top 20 rows
```

```
Column: mqtt_msg
+--------------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------
-------------------------------------------+
|mqtt_msg

                                           |
+--------------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------
-------------------------------------------+
|313934304332664635316145663532453242454437644232373562453946316231393443363833324343443
14231443865423634444343333641656446633461614538416546426346353061646546313465643645334 33
24563646262343834426266                    |
|4542446162316365633264384342653866643566426139616565373835306643613738303133394443314 53
63636636646663063653136374245316236656637374645396133364635346543613644463937364637326 64
5636365                                    |
|3964356332323133339463336453666354135373437303561373436653731353231353042434264666135333
13265303139374231443243443943333132626345643441344165306434663534466462634132633038364 64
435423130384365                            |
|6238444461426362314634616235443561433433623265623341394144654339364238343443664265466 44
54243613831643443623164616341356237344261323239453263433035626137393262663162464161653 53
13537394442393238376532653836 3330          |
|63304463463044326165663931356366324563353764663632393963443565613741326245373041393745 3
34344644435456262343644363245463043424531616436384663634236663143363133444661306532306 53
64236374238414441654446633232              |
|323939.0

                                           |
|4335666366423935393942633565314262334539316144613937394534364261304645613832616332393 24
54334353466303633356564323164464432433332426432393161666264426334353837446443613439653 93
243634266643946416433434561666463          |
|3233663231444145353845356442383266413431644434324366633162453666636136644235623761393 54
54136433846623946373562316237424342443930644461626365433337363543316538346462444335323 06
2616135316537644334456265                  |
|3744424339464144363934634543394641443165393830423630306438384430336633664241413433424 16
34264464439646433313733374663306646393761303935624645614662644131396536443542653045316 36
1376165434339463741313664                  |
|3243373234304263414631366531626465396635664646654637453330353236313543354361613763344 16
53161443461383064314632433238656261643162626146316334344331354134656666653434423444464 33
7414632376533354634356165                  |
|3937304530664246376466464639304441314665443135383230436141613345616142426444373841334 13
03466463831364662446564304641613939423743666538364131433131436166363232664662313835386 13
44361643566                                |
|3561416235464662644139453032623261343043363244453945433134623862646643313165353465413 46
34644346562643743353931643432466238663642433943334345343034346134643146446341363745334 53
63046423041456444633962466133654138        |
|3664613362463741306165386363664465444361363631314131314561666341443166656341663044344 43
24266374142623945646635394630393742454331463143313733364465313744623933383066363435376 33
53364634246316362                          |
|333032

                                           |
|3742326131643332344135444644443532636235634134656265616134413738633242653843464433633 53
73833303730353661333045613142613337303830643241623138354461316135453833616442616442633 34
663444362383539634543                      |
|3943643445433334434438433464623065634162343930396532443244446335663162444166343931663 06
33544613646426630344235353946624366463330353366456639453845304437373245386543366337414 63
731633461413534384436444342                |
|6537334530453042354138633762354166433066333239664136313145643645344161306336353864414 53
64263364635623138463037376534443146433861433146643231463038353262313735304134633332384 44
2303666463262434246356235386231634244466241|
|3532383138356539623734333165663964306130306439626631326444633531343162644633303432436 23
73232653335343537306463624239453463323364443146626439316365463361613538393165333846334 66
461453932656133643139313138                |
|666637354139363333613844356438394166414634466263376665624666354541614546446231316538304
```

```
3463032316330634243393664364444653837433934633844313663623438433744636536346363354634433
76345                                      |
|356643666565633863644566614665463545443637413242346142376344336643646664437383031416139 4
6334230334146316562423342614346303865336466653266644131663145663032643163373641346341373
7394664453437443635                        |
+---------------------------------------------------------------------------------------
----------------------------------------------------------------------------------------
-------------------------------------------+
only showing top 20 rows
```

```
Column: mqtt_msgid
+----------+
|mqtt_msgid|
+----------+
|6653.0    |
|2815.0    |
|692.0     |
|6454.0    |
|7554.0    |
|934.0     |
|4142.0    |
|1761.0    |
|7115.0    |
|3597.0    |
|5983.0    |
|305.0     |
|7782.0    |
|5858.0    |
|8649.0    |
|2734.0    |
|299.0     |
|2862.0    |
|3980.0    |
|6433.0    |
+----------+
only showing top 20 rows
```

```
Column: mqtt_msgtype
+------------+
|mqtt_msgtype|
+------------+
|8.0         |
|0.0         |
|1.0         |
|4.0         |
|14.0        |
|3.0         |
|2.0         |
|13.0        |
|5.0         |
|9.0         |
|12.0        |
+------------+
```

```
Column: mqtt_proto_len
+--------------+
|mqtt_proto_len|
+--------------+
|0.0           |
|4.0           |
```

```
+---------------+


Column: mqtt_protoname
+---------------+
|mqtt_protoname|
+---------------+
|MQTT          |
|0             |
+---------------+


Column: mqtt_qos
+---------+
|mqtt_qos|
+---------+
|0.0     |
|1.0     |
+---------+


Column: mqtt_retain
+------------+
|mqtt_retain|
+------------+
|0.0        |
|1.0        |
+------------+


Column: mqtt_sub_qos
+-------------+
|mqtt_sub_qos|
+-------------+
|0.0         |
+-------------+


Column: mqtt_suback_qos
+----------------+
|mqtt_suback_qos|
+----------------+
|0.0            |
+----------------+


Column: mqtt_ver
+---------+
|mqtt_ver|
+---------+
|0.0     |
|4.0     |
+---------+


Column: mqtt_willmsg
+-------------+
|mqtt_willmsg|
+-------------+
```

```
|0.0          |
+-------------+



Column: mqtt_willmsg_len
+----------------+
|mqtt_willmsg_len|
+----------------+
|0.0             |
+----------------+



Column: mqtt_willtopic
+--------------+
|mqtt_willtopic|
+--------------+
|0.0           |
+--------------+



Column: mqtt_willtopic_len
+------------------+
|mqtt_willtopic_len|
+------------------+
|0.0               |
+------------------+



Column: target
+----------+
|target    |
+----------+
|slowite   |
|bruteforce|
|flood     |
|malformed |
|dos       |
|legitimate|
+----------+



Column: dataset
+-------+
|dataset|
+-------+
|train  |
|test   |
+-------+
```

We can see that there are coloumns with only one unique value. Let's drop these coloumns.

In [87]:

```
df = df.drop("mqtt_conack_flags_reserved","mqtt_conack_flags_sp","mqtt_conflag_qos","mqt
             "mqtt_conflag_retain","mqtt_conflag_willflag","mqtt_sub_qos","mqtt_suback_q
             "mqtt_willmsg_len","mqtt_willtopic","mqtt_willtopic_len")
df.printSchema()
```

```
root
```

```
 |-- tcp_flags: string (nullable = true)
 |-- tcp_time_delta: double (nullable = true)
 |-- tcp_len: integer (nullable = true)
 |-- mqtt_conack_flags: string (nullable = true)
 |-- mqtt_conack_val: double (nullable = true)
 |-- mqtt_conflag_cleansess: double (nullable = true)
 |-- mqtt_conflag_passwd: double (nullable = true)
 |-- mqtt_conflag_uname: double (nullable = true)
 |-- mqtt_conflags: string (nullable = true)
 |-- mqtt_dupflag: double (nullable = true)
 |-- mqtt_hdrflags: string (nullable = true)
 |-- mqtt_kalive: double (nullable = true)
 |-- mqtt_len: double (nullable = true)
 |-- mqtt_msg: string (nullable = true)
 |-- mqtt_msgid: double (nullable = true)
 |-- mqtt_msgtype: double (nullable = true)
 |-- mqtt_proto_len: double (nullable = true)
 |-- mqtt_protoname: string (nullable = true)
 |-- mqtt_qos: double (nullable = true)
 |-- mqtt_retain: double (nullable = true)
 |-- mqtt_ver: double (nullable = true)
 |-- target: string (nullable = true)
 |-- dataset: string (nullable = true)
```

Now, there are binary coloumns which has values as strings, values other than 0 and 1. Therefore, lets encode these coloumns with binary values 0 and 1. Also we will cast these coloumns to datatype double.

In [88]:

```python
from pyspark.sql.functions import col, when

# Note when a coloumn is encoded we will drop the original coloumn.
conversion_map1 = {"0": 0, "0x00000000": 1}
conversion_map2 = {"train": 0, "test": 1}
conversion_map3 = {"0.0": 0, "5.0": 1}
conversion_map4 = {"0.0": 0, "4.0": 1}
conversion_map5 = {"MQTT": 0, "0": 1}

# Note in the below code "mqtt_conack_flags"] == "0" and df["dataset"] == "train" is use
df_binary = df.withColumn("mqtt_conack_flags_encoded_binary", when(df["mqtt_conack_flags
df_binary = df_binary.withColumn("dataset_encoded_binary", when(df["dataset"] == "train"

# Note in the below code df["mqtt_conack_val"] == 0.0 and df["mqtt_proto_len"] == 0.0 is
df_binary = df_binary.withColumn("mqtt_conack_val_encoded_binary", when(df["mqtt_conack_
df_binary = df_binary.withColumn("mqtt_proto_len_encoded_binary", when(df["mqtt_proto_le

# Note in the below code ["mqtt_protoname"] == MQTT is used as its dataype is a string
df_binary = df_binary.withColumn("mqtt_protoname_encoded_binary", when(df["mqtt_protonam

# Casting string datatypes
df_binary = df_binary.withColumn('mqtt_conack_flags_encoded_binary', col('mqtt_conack_fl
df_binary = df_binary.withColumn('dataset_encoded_binary', col('dataset_encoded_binary')
df_binary = df_binary.withColumn('mqtt_protoname_encoded_binary', col('mqtt_protoname_en


df_binary.printSchema()
df = df_binary
```

```
root
 |-- tcp_flags: string (nullable = true)
 |-- tcp_time_delta: double (nullable = true)
 |-- tcp_len: integer (nullable = true)
 |-- mqtt_conflag_cleansess: double (nullable = true)
 |-- mqtt_conflag_passwd: double (nullable = true)
 |-- mqtt_conflag_uname: double (nullable = true)
```

```
 |-- mqtt_conflags: string (nullable = true)
 |-- mqtt_dupflag: double (nullable = true)
 |-- mqtt_hdrflags: string (nullable = true)
 |-- mqtt_kalive: double (nullable = true)
 |-- mqtt_len: double (nullable = true)
 |-- mqtt_msg: string (nullable = true)
 |-- mqtt_msgid: double (nullable = true)
 |-- mqtt_msgtype: double (nullable = true)
 |-- mqtt_qos: double (nullable = true)
 |-- mqtt_retain: double (nullable = true)
 |-- mqtt_ver: double (nullable = true)
 |-- target: string (nullable = true)
 |-- mqtt_conack_flags_encoded_binary: double (nullable = false)
 |-- dataset_encoded_binary: double (nullable = false)
 |-- mqtt_conack_val_encoded_binary: integer (nullable = false)
 |-- mqtt_proto_len_encoded_binary: integer (nullable = false)
 |-- mqtt_protoname_encoded_binary: double (nullable = false)
```

Lets investigate more on the coloumn mqtt_msg

In [89]:
```
unique_values_count = df.select(countDistinct(col('mqtt_msg')).alias('unique_values_coun

print(f"Number of unique values in 'your_column': {unique_values_count}")
```

```
Number of unique values in 'your_column': 50055
```

As we can see this coloumn has roughly half unique values with very large individual dataset numeric value, this coloumn will cause the pipeline to fail. hence dropping this coloumn.

In [90]:
```
df = df.drop("mqtt_msg")
df.printSchema()

num_columns = len(df.columns)

# Print the number of columns
print("Number of columns:", num_columns)
```

```
root
 |-- tcp_flags: string (nullable = true)
 |-- tcp_time_delta: double (nullable = true)
 |-- tcp_len: integer (nullable = true)
 |-- mqtt_conflag_cleansess: double (nullable = true)
 |-- mqtt_conflag_passwd: double (nullable = true)
 |-- mqtt_conflag_uname: double (nullable = true)
 |-- mqtt_conflags: string (nullable = true)
 |-- mqtt_dupflag: double (nullable = true)
 |-- mqtt_hdrflags: string (nullable = true)
 |-- mqtt_kalive: double (nullable = true)
 |-- mqtt_len: double (nullable = true)
 |-- mqtt_msgid: double (nullable = true)
 |-- mqtt_msgtype: double (nullable = true)
 |-- mqtt_qos: double (nullable = true)
 |-- mqtt_retain: double (nullable = true)
 |-- mqtt_ver: double (nullable = true)
 |-- target: string (nullable = true)
 |-- mqtt_conack_flags_encoded_binary: double (nullable = false)
 |-- dataset_encoded_binary: double (nullable = false)
 |-- mqtt_conack_val_encoded_binary: integer (nullable = false)
 |-- mqtt_proto_len_encoded_binary: integer (nullable = false)
 |-- mqtt_protoname_encoded_binary: double (nullable = false)

Number of columns: 22
```

Now, lets classify our variables

In [91]:
```python
nominal_cols = ['tcp_flags','mqtt_conflags','mqtt_hdrflags']
continuous_cols = ['tcp_time_delta','tcp_len','mqtt_len','mqtt_msgid','mqtt_kalive','mqt
binary_cols = ['mqtt_protoname_encoded_binary','mqtt_proto_len_encoded_binary','mqtt_con
```

Summary table for our dataset

In [92]:
```python
df.summary().show(truncate=False, vertical=True)
```

```
-RECORD 0-----------------------------------------------
 summary                         | count
 tcp_flags                       | 131711
 tcp_time_delta                  | 131711
 tcp_len                         | 131711
 mqtt_conflag_cleansess          | 131711
 mqtt_conflag_passwd             | 131711
 mqtt_conflag_uname              | 131711
 mqtt_conflags                   | 131711
 mqtt_dupflag                    | 131711
 mqtt_hdrflags                   | 131711
 mqtt_kalive                     | 131711
 mqtt_len                        | 131711
 mqtt_msgid                      | 131711
 mqtt_msgtype                    | 131711
 mqtt_qos                        | 131711
 mqtt_retain                     | 131711
 mqtt_ver                        | 131711
 target                          | 131711
 mqtt_conack_flags_encoded_binary | 131711
 dataset_encoded_binary          | 131711
 mqtt_conack_val_encoded_binary  | 131711
 mqtt_proto_len_encoded_binary   | 131711
 mqtt_protoname_encoded_binary   | 131711
-RECORD 1-----------------------------------------------
 summary                         | mean
 tcp_flags                       | NULL
 tcp_time_delta                  | 0.3753143669170306
 tcp_len                         | 374.96095998056353
 mqtt_conflag_cleansess          | 0.017667468928183674
 mqtt_conflag_passwd             | 0.007531641244846672
 mqtt_conflag_uname              | 0.007562010765995247
 mqtt_conflags                   | 0.0
 mqtt_dupflag                    | 0.14203065803159948
 mqtt_hdrflags                   | 0.0
 mqtt_kalive                     | 313.2462664469938
 mqtt_len                        | 73.09472253646241
 mqtt_msgid                      | 3528.354070654691
 mqtt_msgtype                    | 3.1146980889978817
 mqtt_qos                        | 0.4132608514095254
 mqtt_retain                     | 9.110856344572587E-4
 mqtt_ver                        | 0.0706698757127347
 target                          | NULL
 mqtt_conack_flags_encoded_binary | 0.016490649983676383
 dataset_encoded_binary          | 0.3213171261322137
 mqtt_conack_val_encoded_binary  | 0.008829938273948266
 mqtt_proto_len_encoded_binary   | 0.017667468928183674
 mqtt_protoname_encoded_binary   | 0.9823325310718163
-RECORD 2-----------------------------------------------
 summary                         | stddev
 tcp_flags                       | NULL
 tcp_time_delta                  | 3.7903190884152833
 tcp_len                         | 1465.4603593992051
 mqtt_conflag_cleansess          | 0.13174012767231089
 mqtt_conflag_passwd             | 0.08645792258572078
 mqtt_conflag_uname              | 0.08663073207067831
```

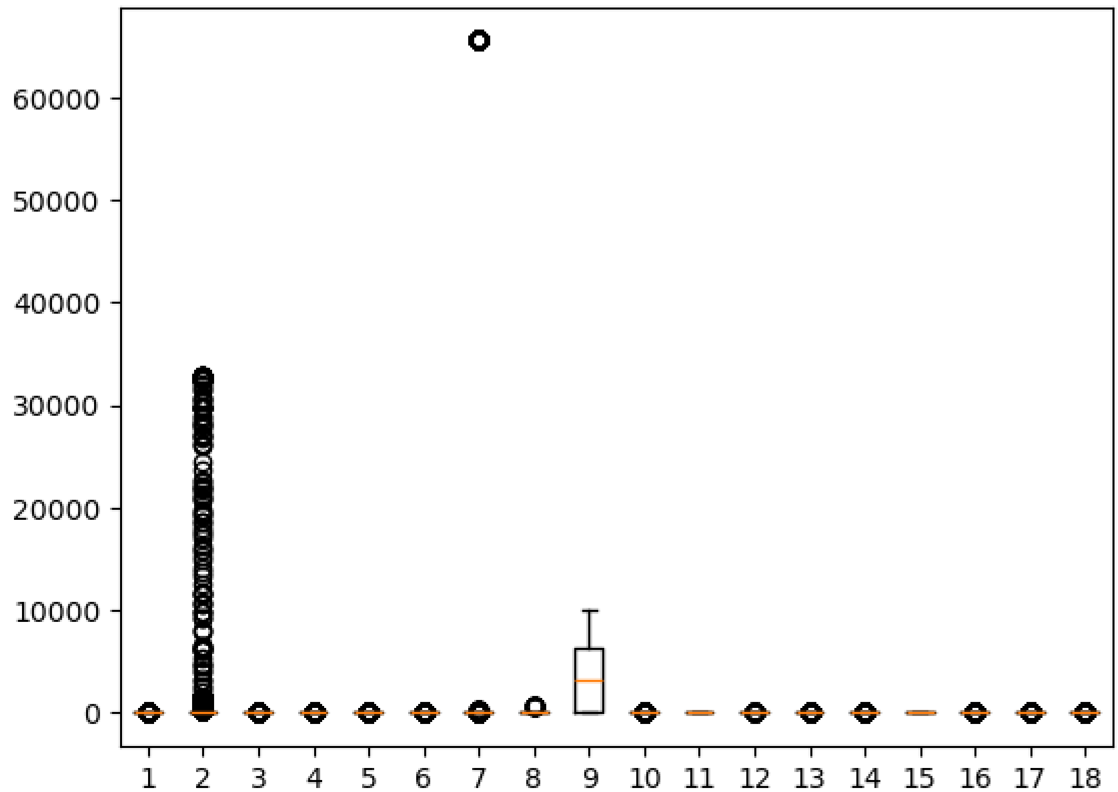
```
 mqtt_conflags                    | 0.0
 mqtt_dupflag                     | 0.3490829062123108
 mqtt_hdrflags                    | 0.0
 mqtt_kalive                      | 4514.4139161100875
 mqtt_len                         | 81.39557465624966
 mqtt_msgid                       | 3262.570804978302
 mqtt_msgtype                     | 1.347649305773393
 mqtt_qos                         | 0.49242071553520866
 mqtt_retain                      | 0.030170556317091108
 mqtt_ver                         | 0.5269605106892435
 target                           | NULL
 mqtt_conack_flags_encoded_binary | 0.12735317658515646
 dataset_encoded_binary           | 0.4669840321550003
 mqtt_conack_val_encoded_binary   | 0.09355232179277516
 mqtt_proto_len_encoded_binary    | 0.13174012767231089
 mqtt_protoname_encoded_binary    | 0.13174012767231086
-RECORD 3-------------------------------------------------
 summary                          | min
 tcp_flags                        | 0x00000002
 tcp_time_delta                   | -2.0E-6
 tcp_len                          | 0
 mqtt_conflag_cleansess           | 0.0
 mqtt_conflag_passwd              | 0.0
 mqtt_conflag_uname               | 0.0
 mqtt_conflags                    | 0
 mqtt_dupflag                     | 0.0
 mqtt_hdrflags                    | 0
 mqtt_kalive                      | 0.0
 mqtt_len                         | 0.0
 mqtt_msgid                       | 0.0
 mqtt_msgtype                     | 0.0
 mqtt_qos                         | 0.0
 mqtt_retain                      | 0.0
 mqtt_ver                         | 0.0
 target                           | bruteforce
 mqtt_conack_flags_encoded_binary | 0.0
 dataset_encoded_binary           | 0.0
 mqtt_conack_val_encoded_binary   | 0
 mqtt_proto_len_encoded_binary    | 0
 mqtt_protoname_encoded_binary    | 0.0
-RECORD 4-------------------------------------------------
 summary                          | 25%
 tcp_flags                        | NULL
 tcp_time_delta                   | 1.0E-6
 tcp_len                          | 8
 mqtt_conflag_cleansess           | 0.0
 mqtt_conflag_passwd              | 0.0
 mqtt_conflag_uname               | 0.0
 mqtt_conflags                    | 0.0
 mqtt_dupflag                     | 0.0
 mqtt_hdrflags                    | 0.0
 mqtt_kalive                      | 0.0
 mqtt_len                         | 2.0
 mqtt_msgid                       | 0.0
 mqtt_msgtype                     | 3.0
 mqtt_qos                         | 0.0
 mqtt_retain                      | 0.0
 mqtt_ver                         | 0.0
 target                           | NULL
 mqtt_conack_flags_encoded_binary | 0.0
 dataset_encoded_binary           | 0.0
 mqtt_conack_val_encoded_binary   | 0
 mqtt_proto_len_encoded_binary    | 0
 mqtt_protoname_encoded_binary    | 1.0
-RECORD 5-------------------------------------------------
 summary                          | 50%
```

```
 tcp_flags                         | NULL
 tcp_time_delta                    | 6.9E-5
 tcp_len                           | 28
 mqtt_conflag_cleansess            | 0.0
 mqtt_conflag_passwd               | 0.0
 mqtt_conflag_uname                | 0.0
 mqtt_conflags                     | 0.0
 mqtt_dupflag                      | 0.0
 mqtt_hdrflags                     | 0.0
 mqtt_kalive                       | 0.0
 mqtt_len                          | 11.0
 mqtt_msgid                        | 3172.0
 mqtt_msgtype                      | 3.0
 mqtt_qos                          | 0.0
 mqtt_retain                       | 0.0
 mqtt_ver                          | 0.0
 target                            | NULL
 mqtt_conack_flags_encoded_binary | 0.0
 dataset_encoded_binary            | 0.0
 mqtt_conack_val_encoded_binary    | 0
 mqtt_proto_len_encoded_binary     | 0
 mqtt_protoname_encoded_binary     | 1.0
-RECORD 6-----------------------------------------------
 summary                           | 75%
 tcp_flags                         | NULL
 tcp_time_delta                    | 8.97E-4
 tcp_len                           | 118
 mqtt_conflag_cleansess            | 0.0
 mqtt_conflag_passwd               | 0.0
 mqtt_conflag_uname                | 0.0
 mqtt_conflags                     | 0.0
 mqtt_dupflag                      | 0.0
 mqtt_hdrflags                     | 0.0
 mqtt_kalive                       | 0.0
 mqtt_len                          | 167.0
 mqtt_msgid                        | 6338.0
 mqtt_msgtype                      | 4.0
 mqtt_qos                          | 1.0
 mqtt_retain                       | 0.0
 mqtt_ver                          | 0.0
 target                            | NULL
 mqtt_conack_flags_encoded_binary | 0.0
 dataset_encoded_binary            | 1.0
 mqtt_conack_val_encoded_binary    | 0
 mqtt_proto_len_encoded_binary     | 0
 mqtt_protoname_encoded_binary     | 1.0
-RECORD 7-----------------------------------------------
 summary                           | max
 tcp_flags                         | 0x00000019
 tcp_time_delta                    | 60.000878
 tcp_len                           | 32768
 mqtt_conflag_cleansess            | 1.0
 mqtt_conflag_passwd               | 1.0
 mqtt_conflag_uname                | 1.0
 mqtt_conflags                     | 0x000000c2
 mqtt_dupflag                      | 1.0
 mqtt_hdrflags                     | 0x000000e0
 mqtt_kalive                       | 65535.0
 mqtt_len                          | 692.0
 mqtt_msgid                        | 10000.0
 mqtt_msgtype                      | 14.0
 mqtt_qos                          | 1.0
 mqtt_retain                       | 1.0
 mqtt_ver                          | 4.0
 target                            | slowite
 mqtt_conack_flags_encoded_binary | 1.0
```

```
dataset_encoded_binary          | 1.0
mqtt_conack_val_encoded_binary  | 1
mqtt_proto_len_encoded_binary   | 1
mqtt_protoname_encoded_binary   | 1.0
```

Boxplots

In [93]:
```python
numeric_features = [feature[0] for feature in df.dtypes if feature[1] in ('int','double'

import matplotlib.pyplot as plt

#Extract data and convert them into Pandas for visualization
converted_data = df[numeric_features].toPandas()

figure = plt.boxplot(converted_data)
```



Lets see outliers and check if we need to handle them.

In [94]:
```python
from functools import reduce

def column_add(a,b):
     return  a.__add__(b)

def find_outliers(df):
    # Identifying the numerical columns in a spark dataframe
    numeric_columns = [column[0] for column in df.dtypes if column[1]=='int']

    # Using the `for` loop to create new columns by identifying the outliers for each fe
    for column in numeric_columns:

        less_Q1 = 'less_Q1_{}'.format(column)
        more_Q3 = 'more_Q3_{}'.format(column)
        Q1 = 'Q1_{}'.format(column)
        Q3 = 'Q3_{}'.format(column)

        # Q1 : First Quartile ., Q3 : Third Quartile
        Q1 = df.approxQuantile(column,[0.25],relativeError=0)
```

```
        Q3 = df.approxQuantile(column,[0.75],relativeError=0)

        # IQR : Inter Quantile Range
        # We need to define the index [0], as Q1 & Q3 are a set of lists., to perform a
        # Q1 & Q3 are defined seperately so as to have a clear indication on First Quant
        IQR = Q3[0] - Q1[0]

        #selecting the data, with -1.5*IQR to + 1.5*IQR., where param = 1.5 default valu
        less_Q1 =  Q1[0] - 1.5*IQR
        more_Q3 =  Q3[0] + 1.5*IQR

        isOutlierCol = 'is_outlier_{}'.format(column)

        df = df.withColumn(isOutlierCol,when((df[column] > more_Q3) | (df[column] < less_


    # Selecting the specific columns which we have added above, to check if there are an
    selected_columns = [column for column in df.columns if column.startswith("is_outlier
    # Adding all the outlier columns into a new colum "total_outliers", to see the total
    df = df.withColumn('total_outliers',reduce(column_add, ( df[col] for col in  selecte

    # Dropping the extra columns created above, just to create nice dataframe., without
    df = df.drop(*[column for column in df.columns if column.startswith("is_outlier")])

    return df

df_with_outlier_handling = find_outliers(df)
df_with_outlier_handling.show(1, vertical=True)

df_with_outlier_handling.groupby("total_outliers").count().show()
```

```
-RECORD 0-------------------------------------------
 tcp_flags                        | 0x00000018
 tcp_time_delta                   | 1.76E-4
 tcp_len                          | 10
 mqtt_conflag_cleansess           | 0.0
 mqtt_conflag_passwd              | 0.0
 mqtt_conflag_uname               | 0.0
 mqtt_conflags                    | 0
 mqtt_dupflag                     | 0.0
 mqtt_hdrflags                    | 0x00000030
 mqtt_kalive                      | 0.0
 mqtt_len                         | 8.0
 mqtt_msgid                       | 0.0
 mqtt_msgtype                     | 3.0
 mqtt_qos                         | 0.0
 mqtt_retain                      | 0.0
 mqtt_ver                         | 0.0
 target                           | legitimate
 mqtt_conack_flags_encoded_binary | 0.0
 dataset_encoded_binary           | 0.0
 mqtt_conack_val_encoded_binary   | 0
 mqtt_proto_len_encoded_binary    | 0
 mqtt_protoname_encoded_binary    | 1.0
 total_outliers                   | 0
only showing top 1 row

+--------------+------+
|total_outliers| count|
+--------------+------+
|             1| 31250|
|             2|    41|
|             0|100420|
+--------------+------+
```

As there are no rows with more than 3 outliers, we will not drop any rows on the basis of outliers.

Correlation Matrix

In [95]:
```python
numeric_columns = [col for col, dtype in df.dtypes if dtype in ['double', 'int']]
numeric_df = df.select(numeric_columns)

# Calculate the correlation matrix
correlation_matrix = numeric_df.toPandas().corr()

# Print the correlation matrix
print(correlation_matrix)
```

```
                                  tcp_time_delta   tcp_len  \
tcp_time_delta                          1.000000 -0.015399
tcp_len                                -0.015399  1.000000
mqtt_conflag_cleansess                 -0.013268 -0.031589
mqtt_conflag_passwd                    -0.008618 -0.020574
mqtt_conflag_uname                     -0.008636 -0.020617
mqtt_dupflag                           -0.034507  0.109376
mqtt_kalive                            -0.006864 -0.017614
mqtt_len                               -0.078447  0.207645
mqtt_msgid                             -0.103342  0.062935
mqtt_msgtype                            0.423612 -0.015667
mqtt_qos                               -0.076878  0.203916
mqtt_retain                            -0.002978  0.004270
mqtt_ver                               -0.013268 -0.031589
mqtt_conack_flags_encoded_binary       -0.012750 -0.032778
dataset_encoded_binary                  0.002419 -0.005156
mqtt_conack_val_encoded_binary         -0.009267 -0.023892
mqtt_proto_len_encoded_binary          -0.013268 -0.031589
mqtt_protoname_encoded_binary           0.013268  0.031589

                                  mqtt_conflag_cleansess  mqtt_conflag_passwd  \
tcp_time_delta                                 -0.013268            -0.008618
tcp_len                                        -0.031589            -0.020574
mqtt_conflag_cleansess                          1.000000             0.649574
mqtt_conflag_passwd                             0.649574             1.000000
mqtt_conflag_uname                              0.650892             0.997975
mqtt_dupflag                                   -0.054565            -0.035444
mqtt_kalive                                     0.517402            -0.004887
mqtt_len                                       -0.061744            -0.049479
mqtt_msgid                                     -0.145035            -0.094211
mqtt_msgtype                                   -0.210441            -0.136697
mqtt_qos                                       -0.112551            -0.073110
mqtt_retain                                    -0.004050            -0.002631
mqtt_ver                                        1.000000             0.649574
mqtt_conack_flags_encoded_binary               -0.017366            -0.011280
dataset_encoded_binary                          0.008182             0.005125
mqtt_conack_val_encoded_binary                 -0.012658            -0.008222
mqtt_proto_len_encoded_binary                   1.000000             0.649574
mqtt_protoname_encoded_binary                  -1.000000            -0.649574

                                  mqtt_conflag_uname  mqtt_dupflag  \
tcp_time_delta                             -0.008636     -0.034507
tcp_len                                    -0.020617      0.109376
mqtt_conflag_cleansess                      0.650892     -0.054565
mqtt_conflag_passwd                         0.997975     -0.035444
mqtt_conflag_uname                          1.000000     -0.035516
mqtt_dupflag                               -0.035516      1.000000
mqtt_kalive                                -0.004897     -0.028232
mqtt_len                                   -0.049600      0.478699
mqtt_msgid                                 -0.094402      0.273875
mqtt_msgtype                               -0.136975     -0.034629
mqtt_qos                                   -0.073258      0.484803
```

```
mqtt_retain                              -0.002636     -0.012287
mqtt_ver                                  0.650892     -0.054565
mqtt_conack_flags_encoded_binary         -0.011303     -0.052685
dataset_encoded_binary                    0.004874      0.025808
mqtt_conack_val_encoded_binary           -0.008239     -0.038403
mqtt_proto_len_encoded_binary             0.650892     -0.054565
mqtt_protoname_encoded_binary            -0.650892      0.054565

                                  mqtt_kalive  mqtt_len  mqtt_msgid  \
tcp_time_delta                      -0.006864 -0.078447   -0.103342
tcp_len                             -0.017614  0.207645    0.062935
mqtt_conflag_cleansess               0.517402 -0.061744   -0.145035
mqtt_conflag_passwd                 -0.004887 -0.049479   -0.094211
mqtt_conflag_uname                  -0.004897 -0.049600   -0.094402
mqtt_dupflag                        -0.028232  0.478699    0.273875
mqtt_kalive                          1.000000 -0.036721   -0.075041
mqtt_len                            -0.036721  1.000000    0.397383
mqtt_msgid                          -0.075041  0.397383    1.000000
mqtt_msgtype                        -0.108883 -0.082780    0.224672
mqtt_qos                            -0.058234  0.986470    0.421840
mqtt_retain                         -0.002095 -0.012609   -0.032658
mqtt_ver                             0.517402 -0.061744   -0.145035
mqtt_conack_flags_encoded_binary    -0.008985 -0.113101   -0.140037
dataset_encoded_binary               0.010912 -0.024177    0.264107
mqtt_conack_val_encoded_binary      -0.006549 -0.082441   -0.102075
mqtt_proto_len_encoded_binary        0.517402 -0.061744   -0.145035
mqtt_protoname_encoded_binary       -0.517402  0.061744    0.145035

                                  mqtt_msgtype  mqtt_qos  mqtt_retain  \
tcp_time_delta                        0.423612 -0.076878    -0.002978
tcp_len                              -0.015667  0.203916     0.004270
mqtt_conflag_cleansess               -0.210441 -0.112551    -0.004050
mqtt_conflag_passwd                  -0.136697 -0.073110    -0.002631
mqtt_conflag_uname                   -0.136975 -0.073258    -0.002636
mqtt_dupflag                         -0.034629  0.484803    -0.012287
mqtt_kalive                          -0.108883 -0.058234    -0.002095
mqtt_len                             -0.082780  0.986470    -0.012609
mqtt_msgid                            0.224672  0.421840    -0.032658
mqtt_msgtype                          1.000000 -0.071428    -0.002570
mqtt_qos                             -0.071428  1.000000    -0.025344
mqtt_retain                          -0.002570 -0.025344     1.000000
mqtt_ver                             -0.210441 -0.112551    -0.004050
mqtt_conack_flags_encoded_binary     -0.107105 -0.108672    -0.003910
dataset_encoded_binary               -0.020692 -0.026896    -0.002456
mqtt_conack_val_encoded_binary       -0.078070 -0.079213    -0.002850
mqtt_proto_len_encoded_binary        -0.210441 -0.112551    -0.004050
mqtt_protoname_encoded_binary         0.210441  0.112551     0.004050

                                  mqtt_ver  mqtt_conack_flags_encoded_binary  \
tcp_time_delta                   -0.013268                         -0.012750
tcp_len                          -0.031589                         -0.032778
mqtt_conflag_cleansess            1.000000                         -0.017366
mqtt_conflag_passwd               0.649574                         -0.011280
mqtt_conflag_uname                0.650892                         -0.011303
mqtt_dupflag                     -0.054565                         -0.052685
mqtt_kalive                       0.517402                         -0.008985
mqtt_len                         -0.061744                         -0.113101
mqtt_msgid                       -0.145035                         -0.140037
mqtt_msgtype                     -0.210441                         -0.107105
mqtt_qos                         -0.112551                         -0.108672
mqtt_retain                      -0.004050                         -0.003910
mqtt_ver                          1.000000                         -0.017366
mqtt_conack_flags_encoded_binary -0.017366                          1.000000
dataset_encoded_binary            0.008182                          0.004098
mqtt_conack_val_encoded_binary   -0.012658                          0.728912
mqtt_proto_len_encoded_binary     1.000000                         -0.017366
```

```
mqtt_protoname_encoded_binary    -1.000000                          0.017366

                                  dataset_encoded_binary  \
tcp_time_delta                                  0.002419
tcp_len                                        -0.005156
mqtt_conflag_cleansess                          0.008182
mqtt_conflag_passwd                             0.005125
mqtt_conflag_uname                              0.004874
mqtt_dupflag                                    0.025808
mqtt_kalive                                     0.010912
mqtt_len                                       -0.024177
mqtt_msgid                                      0.264107
mqtt_msgtype                                   -0.020692
mqtt_qos                                       -0.026896
mqtt_retain                                    -0.002456
mqtt_ver                                        0.008182
mqtt_conack_flags_encoded_binary                0.004098
dataset_encoded_binary                          1.000000
mqtt_conack_val_encoded_binary                 -0.001163
mqtt_proto_len_encoded_binary                   0.008182
mqtt_protoname_encoded_binary                  -0.008182

                                  mqtt_conack_val_encoded_binary  \
tcp_time_delta                                         -0.009267
tcp_len                                                -0.023892
mqtt_conflag_cleansess                                 -0.012658
mqtt_conflag_passwd                                    -0.008222
mqtt_conflag_uname                                     -0.008239
mqtt_dupflag                                           -0.038403
mqtt_kalive                                            -0.006549
mqtt_len                                               -0.082441
mqtt_msgid                                             -0.102075
mqtt_msgtype                                           -0.078070
mqtt_qos                                               -0.079213
mqtt_retain                                            -0.002850
mqtt_ver                                               -0.012658
mqtt_conack_flags_encoded_binary                        0.728912
dataset_encoded_binary                                 -0.001163
mqtt_conack_val_encoded_binary                          1.000000
mqtt_proto_len_encoded_binary                          -0.012658
mqtt_protoname_encoded_binary                           0.012658

                                  mqtt_proto_len_encoded_binary  \
tcp_time_delta                                        -0.013268
tcp_len                                               -0.031589
mqtt_conflag_cleansess                                 1.000000
mqtt_conflag_passwd                                    0.649574
mqtt_conflag_uname                                     0.650892
mqtt_dupflag                                          -0.054565
mqtt_kalive                                            0.517402
mqtt_len                                              -0.061744
mqtt_msgid                                            -0.145035
mqtt_msgtype                                          -0.210441
mqtt_qos                                              -0.112551
mqtt_retain                                           -0.004050
mqtt_ver                                               1.000000
mqtt_conack_flags_encoded_binary                      -0.017366
dataset_encoded_binary                                 0.008182
mqtt_conack_val_encoded_binary                        -0.012658
mqtt_proto_len_encoded_binary                          1.000000
mqtt_protoname_encoded_binary                         -1.000000

                                  mqtt_protoname_encoded_binary
tcp_time_delta                                         0.013268
tcp_len                                                0.031589
mqtt_conflag_cleansess                                -1.000000
```

```
mqtt_conflag_passwd                              -0.649574
mqtt_conflag_uname                               -0.650892
mqtt_dupflag                                      0.054565
mqtt_kalive                                      -0.517402
mqtt_len                                          0.061744
mqtt_msgid                                        0.145035
mqtt_msgtype                                      0.210441
mqtt_qos                                          0.112551
mqtt_retain                                       0.004050
mqtt_ver                                         -1.000000
mqtt_conack_flags_encoded_binary                  0.017366
dataset_encoded_binary                           -0.008182
mqtt_conack_val_encoded_binary                    0.012658
mqtt_proto_len_encoded_binary                    -1.000000
mqtt_protoname_encoded_binary                     1.000000
```

List of correlated columns that needs to be removed.

In [96]:
```
correlated_col = ['mqtt_proto_len_encoded_binary', 'mqtt_protoname_encoded_binary','mqtt
```

Now, let's handle further feature engineering steps including removing correlated columns, one hot encoding, vectorizing the features and outcomes in our pipeline transformer setup.

In [97]:
```
from pyspark.sql.functions import col, when
import pyspark
from pyspark.sql import SparkSession, SQLContext
from pyspark.ml import Pipeline,Transformer
from pyspark.ml.feature import Imputer,StandardScaler,StringIndexer,OneHotEncoder, Vecto

from pyspark.sql.functions import *
from pyspark.sql.types import *
import numpy as np


normal = ['normal']
slowite = ['slowite']
brute_force = ['bruteforce']
flood = ['flood']
malformed = ['malformed']
dos = ['dos']
legitimate = ['legitimate']

class OutcomeCreater(Transformer): # this defines a transformer that creates the outcome

    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
#         label_to_binary = udf(lambda name: 0.0 if name == 'normal' else 1.0 if namdose
#         output_df = dataset.withColumn('outcome', label_to_binary(col('dataset'))).dro
#         output_df = output_df.withColumn('outcome', col('outcome').cast(DoubleType()))
        label_to_binary = udf(lambda name: 0.0 if name == 'normal' else 1.0 if name == '
        output_df = dataset.withColumn('outcome', label_to_binary(col('target'))).drop("
        output_df = output_df.withColumn('outcome', col('outcome').cast(DoubleType()))
#         output_df = output_df.drop('dataset')
#         output_df = output_df.drop('mqtt_msg')
        return output_df

class FeatureTypeCaster(Transformer): # this transformer will cast the columns as approp
    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
        output_df = dataset
```

```
        for col_name in binary_cols + continuous_cols:
            output_df = output_df.withColumn(col_name,col(col_name).cast(DoubleType()))

        return output_df
class ColumnDropper(Transformer): # this transformer drops unnecessary columns
    def __init__(self, columns_to_drop = None):
        super().__init__()
        self.columns_to_drop=columns_to_drop
    def _transform(self, dataset):
        output_df = dataset
        for col_name in self.columns_to_drop:
            output_df = output_df.drop(col_name)
        return output_df

def get_preprocess_pipeline():
    # Stage where columns are casted as appropriate types
#     columns_to_impute = ["tcp_time_delta","tcp_len","mqtt_conack_val","mqtt_conflag_cl
#     imputer1 = Imputer(strategy="median", inputCols=columns_to_impute, outputCols=colu
    stage_typecaster = FeatureTypeCaster()

    # Stage where nominal columns are transformed to index columns using StringIndexer
    nominal_id_cols = [x+"_index" for x in nominal_cols]
    nominal_onehot_cols = [x+"_encoded" for x in nominal_cols]
    stage_nominal_indexer = StringIndexer(inputCols = nominal_cols, outputCols = nominal_

    # Stage where the index columns are further transformed using OneHotEncoder
    stage_nominal_onehot_encoder = OneHotEncoder(inputCols=nominal_id_cols, outputCols=n

    # Stage where all relevant features are assembled into a vector (and dropping a few)
    feature_cols = continuous_cols+binary_cols+nominal_onehot_cols
    corelated_cols_to_remove = correlated_col
    for col_name in corelated_cols_to_remove:
        feature_cols.remove(col_name)
    stage_vector_assembler = VectorAssembler(inputCols=feature_cols, outputCol="vectoriz

    # Stage where we scale the columns
    stage_scaler = StandardScaler(inputCol= 'vectorized_features', outputCol= 'features'

    # Stage for creating the outcome column representing whether there is attack
    stage_outcome = OutcomeCreater()

    # Removing all unnecessary columbs, only keeping the 'features' and 'outcome' column
    stage_column_dropper = ColumnDropper(columns_to_drop = nominal_cols+nominal_id_cols+
        nominal_onehot_cols+ binary_cols + continuous_cols + ['vectorized_features'])
    # Connect the columns into a pipeline
    pipeline = Pipeline(stages=[stage_typecaster,stage_nominal_indexer,stage_nominal_one
        stage_vector_assembler,stage_scaler,stage_outcome,stage_column_dropper])
    return pipeline
```

In [98]:

```
from pyspark.sql.functions import col, when
import os
import sys

os.environ['PYSPARK_PYTHON'] = sys.executable
os.environ['PYSPARK_DRIVER_PYTHON'] = sys.executable

spark = SparkSession.builder \
    .master("local[*]") \
    .appName("SystemsToolChains") \
    .getOrCreate()
```

Load the training and test dataframe using the pipeline

In [99]:

```
column_names = df.columns
```

```
split_column = 'dataset_encoded_binary'

train_set = df.filter(col(split_column) == '0').toDF(*column_names)
test_set = df.filter(col(split_column) == '1').toDF(*column_names)
```

Creating a preprocess pipeline for train and test dataset

In [100…
```
preprocess_pipeline = get_preprocess_pipeline()
preprocess_pipeline_model = preprocess_pipeline.fit(train_set)
```

In [101…
```
pipeline_df = preprocess_pipeline_model.transform(train_set)
pipeline_df_test = preprocess_pipeline_model.transform(test_set)
```

In [102…
```
pipeline_df.printSchema()
pipeline_df.show()
```

```
root
 |-- features: vector (nullable = true)
 |-- outcome: double (nullable = true)

+--------------------+-------+
|            features|outcome|
+--------------------+-------+
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,2,4,12,1...|    5.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,2,4,12,1...|    5.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,2,4,13,1...|    5.0|
|(35,[0,15,19,26],...|    2.0|
|(35,[0,1,2,4,13,1...|    5.0|
|(35,[0,1,2,4,12,1...|    5.0|
|(35,[0,1,2,4,12,1...|    5.0|
|(35,[0,1,2,4,13,1...|    5.0|
|(35,[0,1,4,12,19,...|    6.0|
|(35,[0,1,2,4,12,1...|    5.0|
|(35,[0,17,19,26],...|    4.0|
|(35,[0,14,19,26],...|    1.0|
|(35,[0,1,2,4,10,1...|    5.0|
+--------------------+-------+
only showing top 20 rows
```

Using logistic regression as the first classification model.

First we are fitting the model

In [103…
```
from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression(featuresCol = 'features', labelCol = 'outcome')

lrModel = lr.fit(pipeline_df) # fit the logistic regression model to the training datase
```

Creating predicitions based on the anove model

In [104…
```
predictions = lrModel.transform(pipeline_df_test)
```

In [105…
```
predictions.printSchema()
```

```
root
 |-- features: vector (nullable = true)
 |-- outcome: double (nullable = true)
 |-- rawPrediction: vector (nullable = true)
 |-- probability: vector (nullable = true)
 |-- prediction: double (nullable = false)
```

In [106…
```
predictions.select("rawPrediction","probability","prediction","outcome").toPandas().head
```

Out[106]:

	rawPrediction	probability	prediction	outcome
0	[-7.166962076912546, -5.876349327388862, -6.85...	[1.948719047270581e-10, 7.083619510801849e-10,...	6.0	6.0
1	[-7.1669699484134854, -5.876685471368786, -6.8...	[1.9224227451524251e-10, 6.985738502666139e-10...	6.0	6.0
2	[-7.166962077304591, -5.876349321946417, -6.85...	[1.9487213658971553e-10, 7.083627980369471e-10...	6.0	6.0
3	[-7.085424530771235, 1.0331324243656574, -1.69...	[2.8019457520356055e-13, 9.40381787224079e-10,...	5.0	5.0
4	[-7.0935586092558625, 0.5526896732776247, -2.1...	[1.6541730296138745e-12, 3.4618191178327303e-0...	5.0	5.0

Test and Train accuracy

In [107…
```
predictions_train = lrModel.transform(pipeline_df)# predictions using the training datas
accuracy_train = (predictions_train.filter(predictions_train.outcome == predictions_trai
    .count() / float(predictions_train.count()))

accuracy_test = (predictions.filter(predictions.outcome == predictions.prediction)
    .count() / float(predictions.count()))
print(f"Train Accuracy : {np.round(accuracy_train*100,2)}%")
print(f"Test Accuracy : {np.round(accuracy_test*100,2)}%")
```

```
Train Accuracy : 95.67%
Test Accuracy : 95.38%
```

Confusion Matrix

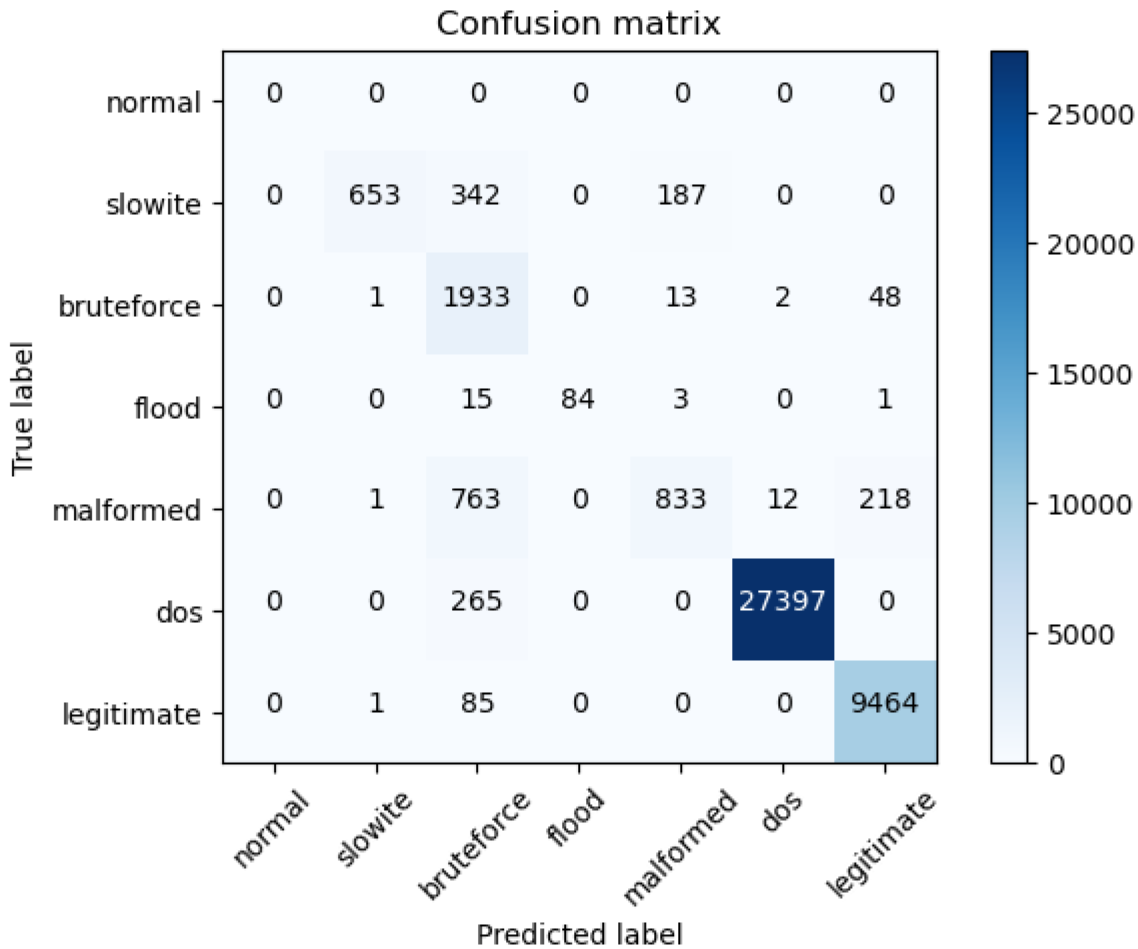
In [108…
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix

import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
```

```python
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [109…

```python
class_names=[0.0,1.0,2.0,3.0,4.0,5.0,6.0]
class_names_str=["normal","slowite", "bruteforce", "flood", "malformed","dos","legitimat

outcome_true = predictions.select("outcome")
outcome_true = outcome_true.toPandas()

pred = predictions.select("prediction")
pred = pred.toPandas()

cnf_matrix = confusion_matrix(outcome_true, pred,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names_str,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[    0     0     0     0     0     0     0]
 [    0   653   342     0   187     0     0]
 [    0     1  1933     0    13     2    48]
 [    0     0    15    84     3     0     1]
 [    0     1   763     0   833    12   218]
 [    0     0   265     0     0 27397     0]
 [    0     1    85     0     0     0  9464]]
```



AUC

In [110…

```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

evaluator = MulticlassClassificationEvaluator(predictionCol='prediction', labelCol='outc
print("Area under the curve/Accuracy is: ", evaluator.evaluate(predictions))
```

```
Area under the curve/Accuracy is:  0.9527723859696371
```

Cross-validation

In [111…

```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

lr = LogisticRegression(featuresCol = 'features', labelCol = 'outcome')

# Create ParamGrid for Cross Validation
lr_paramGrid = (ParamGridBuilder()
             .addGrid(lr.regParam, [0.0001, 0.001, 0.1])
             .addGrid(lr.maxIter, [10, 100, 1000])
             .build())

evaluator = MulticlassClassificationEvaluator(predictionCol='prediction', labelCol='outc

# Create a CrossValidator for multi-class classification
lr_cv = CrossValidator(estimator=lr, estimatorParamMaps=lr_paramGrid, evaluator=evaluato

# Fit the CrossValidator to your data
cv_model = lr_cv.fit(pipeline_df)

# Make predictions on your test data
predictions = cv_model.transform(pipeline_df_test)
```

```
# Evaluate the model's performance using the F1 score or other relevant metrics
f1_score = evaluator.evaluate(predictions)

print(predictions)
```

```
DataFrame[features: vector, outcome: double, rawPrediction: vector, probability: vector,
prediction: double]
```

In [112…

```
print(f"Area under the curve/Accuracy is: {f1_score}")
```

```
Area under the curve/Accuracy is: 0.9519496559358951
```

Random Forrest Classifier is our second classification model

In [113…

```
from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(featuresCol = 'features', labelCol = 'outcome')
rf_model = rf.fit(pipeline_df)
```

In [114…

```
predictions = rf_model.transform(pipeline_df_test)
```

In [115…

```
predictions.printSchema()
```

```
root
 |-- features: vector (nullable = true)
 |-- outcome: double (nullable = true)
 |-- rawPrediction: vector (nullable = true)
 |-- probability: vector (nullable = true)
 |-- prediction: double (nullable = false)
```

In [116…

```
predictions.select("rawPrediction","probability","prediction","outcome").toPandas().head
```

Out[116]:

	rawPrediction	probability	prediction	outcome
0	[0.0, 0.07907099106069214, 0.14001049396305537...	[0.0, 0.0039535495530346075, 0.007000524698152...	6.0	6.0
1	[0.0, 0.07907099106069214, 0.14001049396305537...	[0.0, 0.0039535495530346075, 0.007000524698152...	6.0	6.0
2	[0.0, 0.07907099106069214, 0.14001049396305537...	[0.0, 0.0039535495530346075, 0.007000524698152...	6.0	6.0
3	[0.0, 0.01987669758920522, 0.01685229883386163...	[0.0, 0.000993834879460261, 0.0008426149416930...	5.0	5.0
4	[0.0, 0.01987669758920522, 0.01685229883386163...	[0.0, 0.000993834879460261, 0.0008426149416930...	5.0	5.0

Test and Train accuracy

In [117…

```
rf_prediction_train = rf_model.transform(pipeline_df)
rf_prediction_test = rf_model.transform(pipeline_df_test)

rf_accuracy_train = (rf_prediction_train.filter(rf_prediction_train.outcome == rf_predic
    .count()/ float(rf_prediction_train.count()))
rf_accuracy_test = (rf_prediction_test.filter(rf_prediction_test.outcome == rf_predictio
    .count() / float(rf_prediction_test.count()))

rf_auc = evaluator.evaluate(rf_prediction_test)

print(f"Train accuracy = {np.round(rf_accuracy_train*100,2)}%, test accuracy = {np.round
```

```
Train accuracy = 94.59%, test accuracy = 94.09%
```

Confusion Matrix

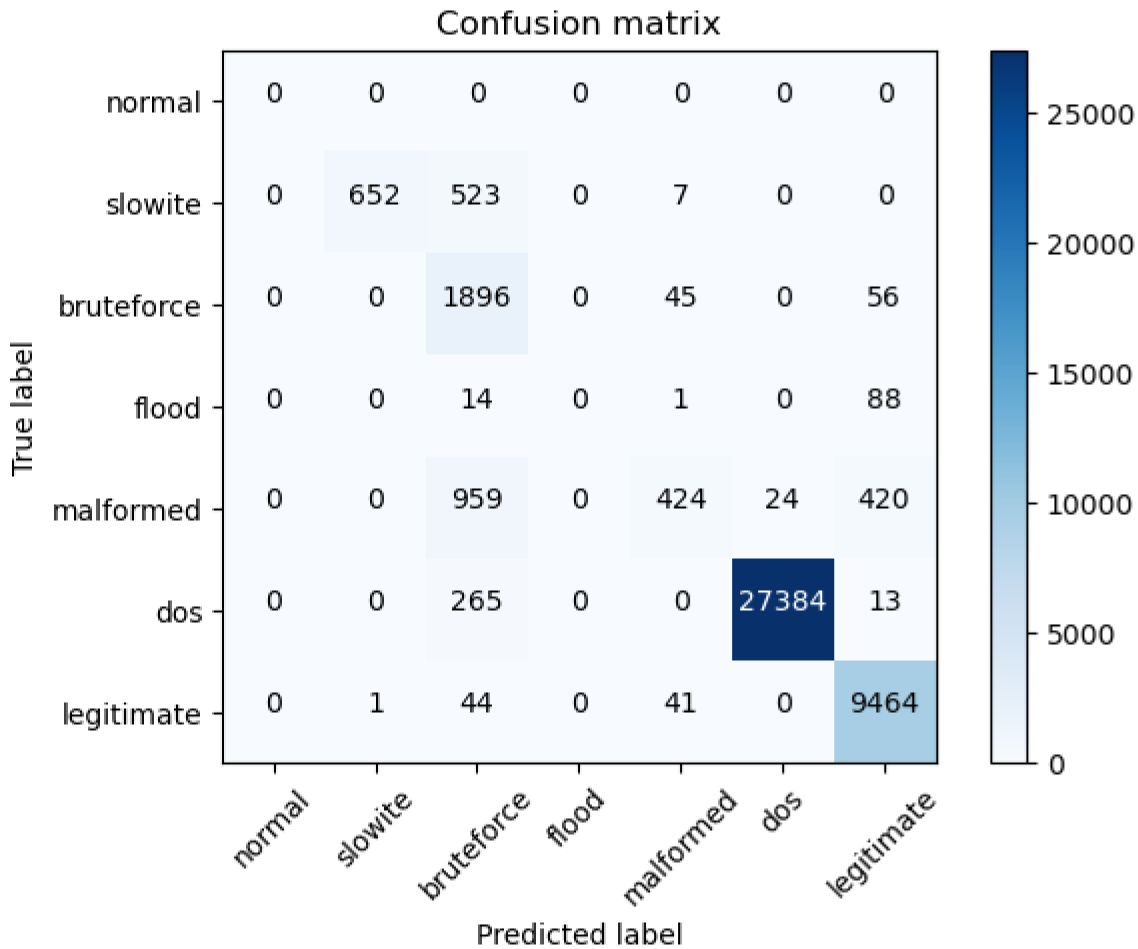
In [118…

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix

import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [119…

```
class_names=[0.0,1.0,2.0,3.0,4.0,5.0,6.0]
class_names_str=["normal","slowite", "bruteforce", "flood", "malformed","dos","legitimat

outcome_true = predictions.select("outcome")
outcome_true = outcome_true.toPandas()

pred = predictions.select("prediction")
pred = pred.toPandas()

cnf_matrix = confusion_matrix(outcome_true, pred,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names_str,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[    0     0     0     0     0     0     0]
 [    0   652   523     0     7     0     0]
 [    0     0  1896     0    45     0    56]
 [    0     0    14     0     1     0    88]
 [    0     0   959     0   424    24   420]
 [    0     0   265     0     0 27384    13]
 [    0     1    44     0    41     0  9464]]
```



Cross validation

In [120…
```
rf_paramGrid = (ParamGridBuilder()
             .addGrid(rf.maxDepth, [5, 10, 15])# maximum depth for each tree
             .addGrid(rf.numTrees,[10, 20, 40])# number of trues
             .build())

rf_cv = CrossValidator(estimator=rf, estimatorParamMaps=rf_paramGrid,
                    evaluator=evaluator, numFolds=5)

rf_cv_model = rf_cv.fit(pipeline_df)

rf_cv_prediction_test = rf_cv_model.transform(pipeline_df_test)
rf_cv_auc = evaluator.evaluate(rf_cv_prediction_test)
```

In [121…
```
print(f"Before cross-validation and parameter tuning, AUC/accuracy={np.round(rf_auc,2)}"
print(f"After cross-validation and parameter tuning, AUC/accuracy={np.round(rf_cv_auc,2)
```

```
Before cross-validation and parameter tuning, AUC/accuracy=0.93
After cross-validation and parameter tuning, AUC/accuracy=0.95
```

Pytorch ML modelling

Creating the pipeline and splitting our dataset to validation_data and test_data

In [122…
```
import pyspark
from pyspark.sql import SparkSession, SQLContext
from pyspark.ml import Pipeline, Transformer
from pyspark.ml.feature import Imputer, StandardScaler, StringIndexer, OneHotEncoder, Ve
from pyspark.sql.functions import *
from pyspark.sql.types import *
import numpy as np
```

```
import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader, TensorDataset

# Convert Spark DataFrames to Pandas DataFrames
nslkdd_pd = pipeline_df.toPandas()
nslkdd_test_pd = pipeline_df_test.toPandas()

# Split the data into training, validation, and testing sets
# 50% of KDDTest+ for validation and the remaining 50% for testing
split_ratio = 0.5
split_index = int(len(nslkdd_test_pd) * split_ratio)

validation_data = nslkdd_test_pd[:split_index]
test_data = nslkdd_test_pd[split_index:]
```

Creating tensors of train, test and validate datasets.

In [123…

```
x_train = torch.from_numpy(np.array(nslkdd_pd['features'].values.tolist(),np.float32))
y_train = torch.from_numpy(np.array(nslkdd_pd['outcome'].values.tolist(),np.int64))
x_validate = torch.from_numpy(np.array(validation_data['features'].values.tolist(),np.fl
y_validate = torch.from_numpy(np.array(validation_data['outcome'].values.tolist(),np.int
x_test = torch.from_numpy(np.array(test_data['features'].values.tolist(),np.float32))
y_test = torch.from_numpy(np.array(test_data['outcome'].values.tolist(),np.int64))
```

In [124…

```
print(x_train.shape)
```

```
torch.Size([89390, 35])
```

In [125…

```
from torch.utils.data import Dataset, DataLoader, TensorDataset

class MyDataset(Dataset):
    def __init__(self,x,y):
        self.x = x
        self.y = y
    def __len__(self):
        return self.x.shape[0]
    def __getitem__(self,idx):
        return (self.x[idx],self.y[idx])

train_dataset = MyDataset(x_train,y_train)
validate_dataset = MyDataset(x_validate,y_validate)
test_dataset = MyDataset(x_test,y_test)
```

Deep Neural Network

Neural Network framework

In [126…

```
import torch.nn as nn

class myMultilayerPerceptron(nn.Module):
    def __init__(self,input_dm,output_dm):
        super().__init__()
        self.sequential = nn.Sequential(
            nn.Linear(input_dm,60),
            nn.Tanh(),
            nn.Linear(60,30),
            nn.Tanh(),
            nn.Linear(30,15),
            nn.Tanh(),
            nn.Linear(15,7),
            nn.Tanh(),
            nn.Linear(7,output_dm)
```

```
        )
    def forward(self,x):
        y = self.sequential(x)
        return y
```

Initializing instance of our model

In [127…

```
mymodel = myMultilayerPerceptron(x_train.shape[1],7)
print(mymodel)
```

```
myMultilayerPerceptron(
  (sequential): Sequential(
    (0): Linear(in_features=35, out_features=60, bias=True)
    (1): Tanh()
    (2): Linear(in_features=60, out_features=30, bias=True)
    (3): Tanh()
    (4): Linear(in_features=30, out_features=15, bias=True)
    (5): Tanh()
    (6): Linear(in_features=15, out_features=7, bias=True)
    (7): Tanh()
    (8): Linear(in_features=7, out_features=7, bias=True)
  )
)
```

In [128…

```
# hyperparameters
lr = 0.1
batch_size = 64
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
```

```
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.22676397860050201,validate_loss=0.20003299415111542
Train_accuracy=92.13%,validate_accuracy=91.92%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.19447417557239532,validate_loss=0.23981551826000214
Train_accuracy=93.02%,validate_accuracy=92.98%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.20002785325050354,validate_loss=0.22096838057041168
Train_accuracy=93.12%,validate_accuracy=92.01%
Epoch=3,train_loss=0.2021917849779129,validate_loss=0.233767569065094
Train_accuracy=93.1%,validate_accuracy=92.98%
Current epoch is best so far, saving model...
Epoch=4,train_loss=0.21347017586231232,validate_loss=0.3639950454235077
Train_accuracy=92.81%,validate_accuracy=89.56%
Epoch=5,train_loss=0.7952061891555786,validate_loss=0.922766923904419
Train_accuracy=75.66%,validate_accuracy=67.6%
Epoch=6,train_loss=0.8437505960464478,validate_loss=0.9514089226722717
Train_accuracy=73.72%,validate_accuracy=67.58%
Epoch=7,train_loss=0.8450164198875427,validate_loss=0.930226743221283
Train_accuracy=73.77%,validate_accuracy=67.58%
Epoch=8,train_loss=0.8448234796524048,validate_loss=0.9507637023925781
Train_accuracy=73.74%,validate_accuracy=67.31%
Epoch=9,train_loss=0.8478856086730957,validate_loss=0.9357566237449646
Train_accuracy=73.67%,validate_accuracy=67.58%
```

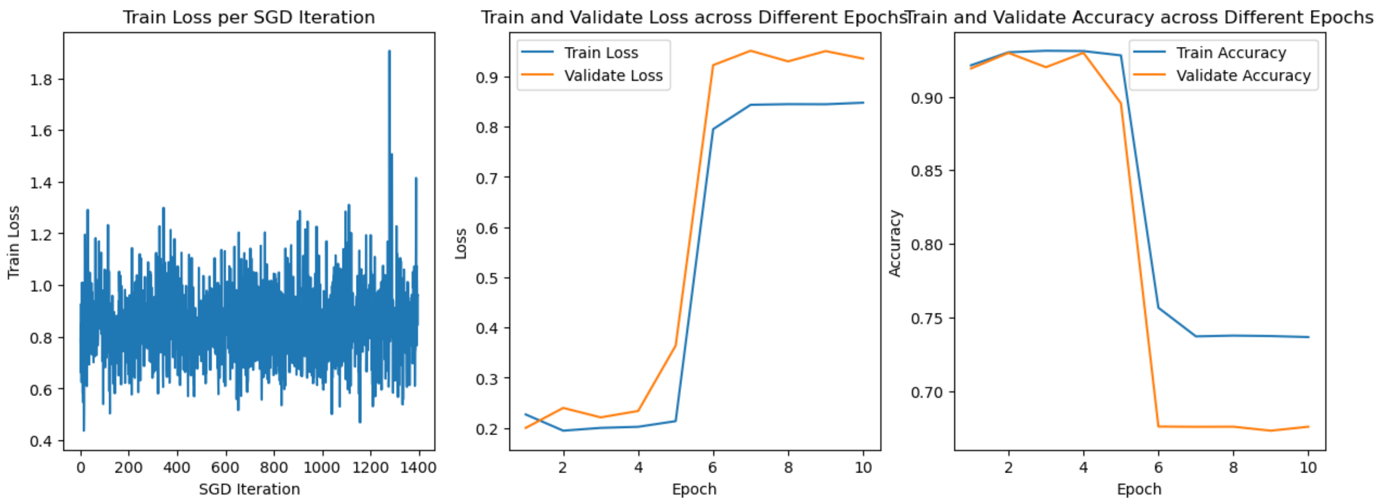
In [129…

```
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
```

```python
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[129]:

```
<function matplotlib.pyplot.tight_layout(*, pad: 'float' = 1.08, h_pad: 'float | None'
= None, w_pad: 'float | None' = None, rect: 'tuple[float, float, float, float] | None'
= None) -> 'None'>
```



Hypertuning it

In [130…

```python
# hyperparameters
lr = 0.05
batch_size = 128
N_epochs = 15

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []
```

```
    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.6121366620063782,validate_loss=0.40193572640419006
Train_accuracy=80.6%,validate_accuracy=87.61%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.32570281624794006,validate_loss=0.39745229482650757
Train_accuracy=89.26%,validate_accuracy=87.68%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.6037207245826721,validate_loss=0.8765270113945007
Train_accuracy=80.74%,validate_accuracy=67.83%
Epoch=3,train_loss=0.7897631525993347,validate_loss=0.889408528804779
Train_accuracy=74.1%,validate_accuracy=68.17%
Epoch=4,train_loss=0.7913605570793152,validate_loss=0.8850198984146118
Train_accuracy=74.01%,validate_accuracy=67.82%
Epoch=5,train_loss=0.7892041206359863,validate_loss=0.898038387298584
Train_accuracy=74.12%,validate_accuracy=67.8%
Epoch=6,train_loss=0.7905600070953369,validate_loss=0.8897964358329773
Train_accuracy=74.05%,validate_accuracy=68.21%
Epoch=7,train_loss=0.7880264520645142,validate_loss=0.8850899338722229
Train_accuracy=74.06%,validate_accuracy=67.8%
Epoch=8,train_loss=0.7892974019050598,validate_loss=0.8708387613296509
Train_accuracy=74.07%,validate_accuracy=67.79%
Epoch=9,train_loss=0.7881177067756653,validate_loss=0.9086756110191345
Train_accuracy=74.07%,validate_accuracy=67.77%
Epoch=10,train_loss=0.7885481715202332,validate_loss=0.88712078332901
Train_accuracy=74.09%,validate_accuracy=67.81%
Epoch=11,train_loss=0.7882986664772034,validate_loss=0.8810194730758667
Train_accuracy=74.09%,validate_accuracy=68.22%
Epoch=12,train_loss=0.7899081110954285,validate_loss=0.885246992111206
Train_accuracy=74.09%,validate_accuracy=67.8%
```

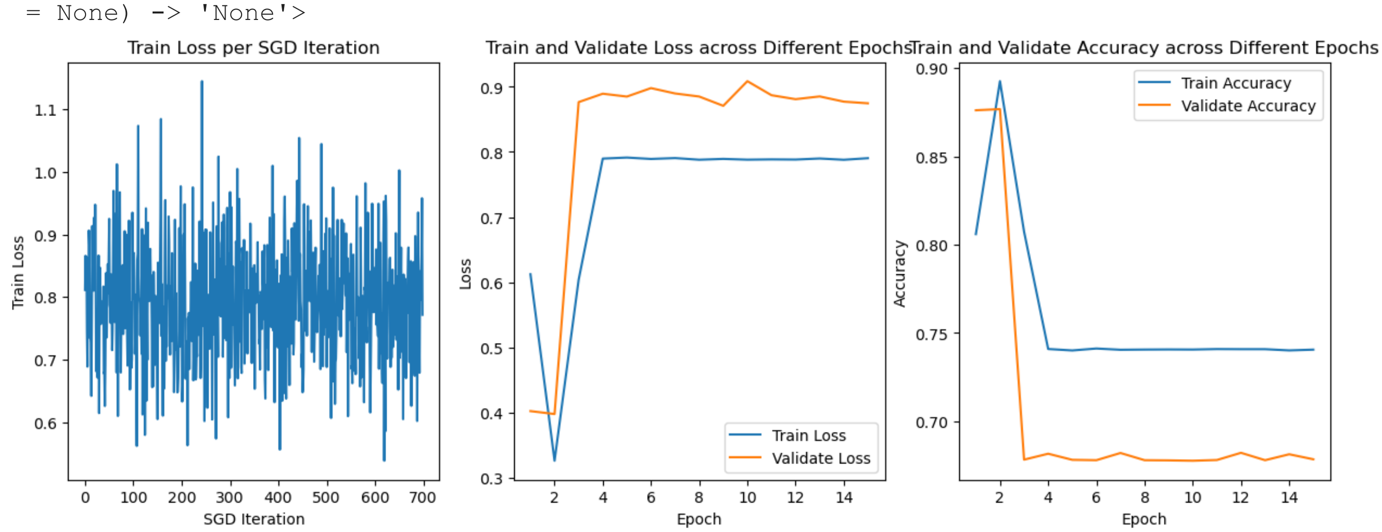
```
Epoch=13,train_loss=0.7879565358161926,validate_loss=0.8772379159927368
Train_accuracy=74.02%,validate_accuracy=68.14%
Epoch=14,train_loss=0.7903791069984436,validate_loss=0.8747062087059021
Train_accuracy=74.06%,validate_accuracy=67.85%
```

In [131…

```python
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[131]:

```
<function matplotlib.pyplot.tight_layout(*, pad: 'float' = 1.08, h_pad: 'float | None'
= None, w_pad: 'float | None' = None, rect: 'tuple[float, float, float, float] | None'
= None) -> 'None'>
```



In [132…

```python
# Load the best model
mybestmodel = myMultilayerPerceptron(x_train.shape[1],7)
mybestmodel.load_state_dict(torch.load("current_best_model"))

test_dataloader = DataLoader(test_dataset, batch_size = batch_size, shuffle = True)
```

```
test_batch_accuracy = []

for x_batch, y_batch in test_dataloader:
    prediction_score = mybestmodel(x_batch)
    prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
    test_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape

test_accuracy = np.mean(np.array(test_batch_accuracy))

print(f"Test accuracy = {np.round(test_accuracy*100,2)}%")
```

```
Test accuracy = 86.95%
```

Shallow Model

Neural Network framework

In [133…

```
import torch.nn as nn

class myMultilayerPerceptron(nn.Module):
    def __init__(self,input_dm,output_dm):
        super().__init__()
        self.sequential = nn.Sequential(
            nn.Linear(input_dm,30),
            nn.Tanh(),
            nn.Linear(30,15),
            nn.Tanh(),
            nn.Linear(15,output_dm)
        )
    def forward(self,x):
        y = self.sequential(x)
        return y
```

In [134…

```
mymodel = myMultilayerPerceptron(x_train.shape[1],7)
print(mymodel)
```

```
myMultilayerPerceptron(
  (sequential): Sequential(
    (0): Linear(in_features=35, out_features=30, bias=True)
    (1): Tanh()
    (2): Linear(in_features=30, out_features=15, bias=True)
    (3): Tanh()
    (4): Linear(in_features=15, out_features=7, bias=True)
  )
)
```

In [135…

```
# hyperparameters
lr = 0.05
batch_size = 64
N_epochs = 10

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []
```

```python
current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.1419348120689392,validate_loss=0.1641492247581482
Train_accuracy=94.88%,validate_accuracy=95.58%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.13145624101161957,validate_loss=0.14668823778629303
Train_accuracy=95.0%,validate_accuracy=94.97%
Epoch=2,train_loss=0.12162972241640091,validate_loss=0.161320760846138
Train_accuracy=95.37%,validate_accuracy=94.35%
Epoch=3,train_loss=0.13050733506679535,validate_loss=0.158644437789917
Train_accuracy=95.09%,validate_accuracy=94.65%
Epoch=4,train_loss=0.13148288428783417,validate_loss=0.15290473401546478
Train_accuracy=94.99%,validate_accuracy=95.12%
Epoch=5,train_loss=0.1224936917424202,validate_loss=0.16370399296283722
Train_accuracy=95.35%,validate_accuracy=94.43%
Epoch=6,train_loss=0.12530523538589478,validate_loss=0.15051129460334778
Train_accuracy=95.28%,validate_accuracy=95.33%
Epoch=7,train_loss=0.12626570463180542,validate_loss=0.1598827838897705
Train_accuracy=95.1%,validate_accuracy=95.03%
Epoch=8,train_loss=0.12178421020507812,validate_loss=0.15547515451908112
Train_accuracy=95.34%,validate_accuracy=95.63%
Current epoch is best so far, saving model...
```

```
Epoch=9,train_loss=0.13378523290157318,validate_loss=0.19341303408145905
Train_accuracy=95.02%,validate_accuracy=94.37%
```

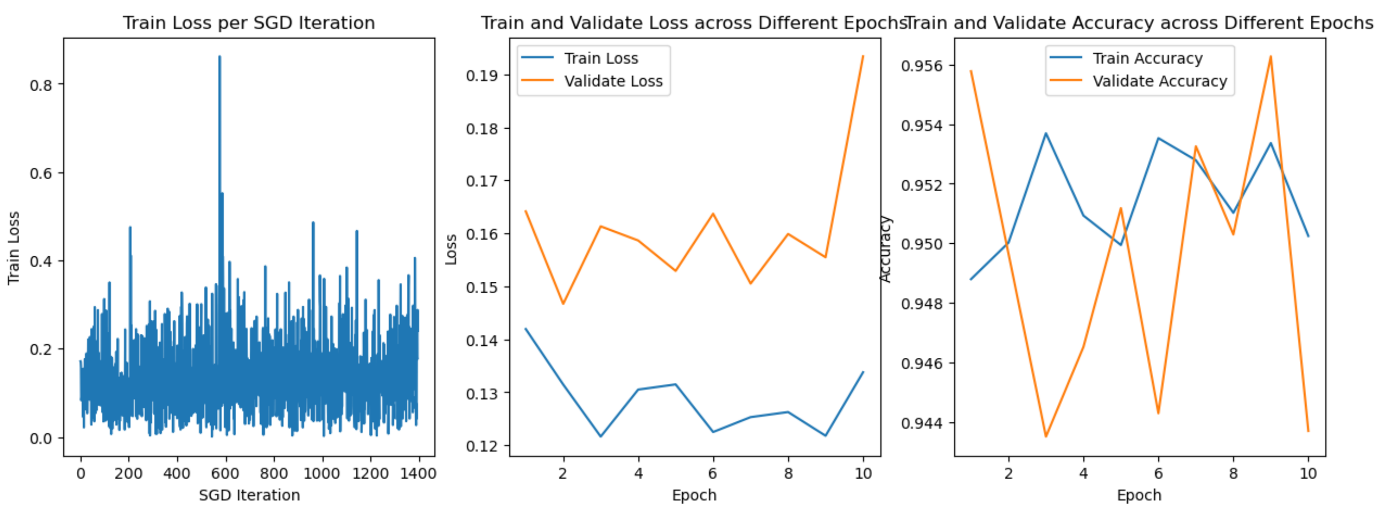
Output plots

In [136…

```python
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()

# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[136]:

```
<function matplotlib.pyplot.tight_layout(*, pad: 'float' = 1.08, h_pad: 'float | None'
= None, w_pad: 'float | None' = None, rect: 'tuple[float, float, float, float] | None'
= None) -> 'None'>
```



Hypertuning it

In [137…

```python
# hyperparameters
lr = 0.001
```

```python
batch_size = 128
N_epochs = 50

loss_fun = nn.CrossEntropyLoss()

train_dataloader = DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
validate_dataloader = DataLoader(validate_dataset, batch_size = batch_size, shuffle = Tr

# Adam Optimizer
optimizer = torch.optim.Adam(mymodel.parameters(),lr = lr)

losses = []
accuracies = []

validate_losses = []
validate_accuracies = []

current_best_accuracy = 0.0

import numpy as np
for epoch in range(N_epochs):

    batch_loss = []
    batch_accuracy = []

    for x_batch,y_batch in train_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        batch_loss.append(loss.detach().numpy())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape[

    validate_batch_loss = []
    validate_batch_accuracy = []

    for x_batch,y_batch in validate_dataloader:
        prediction_score = mymodel(x_batch)
        loss = loss_fun(prediction_score,y_batch)
        validate_batch_loss.append(loss.detach())
        prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
        validate_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_bat

    losses.append(np.mean(np.array(batch_loss)))
    validate_losses.append(np.mean(np.array(validate_batch_loss)))

    accuracies.append(np.mean(np.array(batch_accuracy)))
    validate_accuracies.append(np.mean(np.array(validate_batch_accuracy)))

    print(f"Epoch={epoch},train_loss={losses[-1]},validate_loss={validate_losses[-1]}")
    print(f"Train_accuracy={np.round(accuracies[-1]*100,2)}%,validate_accuracy={np.round




    if validate_accuracies[-1]>current_best_accuracy:
        print("Current epoch is best so far, saving model...")
        torch.save(mymodel.state_dict(),'current_best_model')
        current_best_accuracy = validate_accuracies[-1]
```

```
Epoch=0,train_loss=0.1245306208729744,validate_loss=0.154242590069770８
Train_accuracy=95.38%,validate_accuracy=95.1%
Current epoch is best so far, saving model...
Epoch=1,train_loss=0.11770651489496231,validate_loss=0.15358078479766846
```

```
Train_accuracy=95.46%,validate_accuracy=95.12%
Current epoch is best so far, saving model...
Epoch=2,train_loss=0.11714580655097961,validate_loss=0.15288476645946503
Train_accuracy=95.46%,validate_accuracy=95.11%
Epoch=3,train_loss=0.11672534793615341,validate_loss=0.15136821568012238
Train_accuracy=95.47%,validate_accuracy=95.11%
Epoch=4,train_loss=0.11650104075670242,validate_loss=0.15230758488178253
Train_accuracy=95.48%,validate_accuracy=95.11%
Epoch=5,train_loss=0.11637689918279648,validate_loss=0.15063975751399994
Train_accuracy=95.48%,validate_accuracy=95.1%
Epoch=6,train_loss=0.11610633134841919,validate_loss=0.14960314333438873
Train_accuracy=95.48%,validate_accuracy=95.15%
Current epoch is best so far, saving model...
Epoch=7,train_loss=0.11543701589107513,validate_loss=0.14883415400981903
Train_accuracy=95.48%,validate_accuracy=95.11%
Epoch=8,train_loss=0.11482033878564835,validate_loss=0.14887768030166626
Train_accuracy=95.5%,validate_accuracy=95.14%
Epoch=9,train_loss=0.11360035091638565,validate_loss=0.14477820694446564
Train_accuracy=95.49%,validate_accuracy=95.1%
Epoch=10,train_loss=0.11060910671949387,validate_loss=0.14335279166698456
Train_accuracy=95.47%,validate_accuracy=95.1%
Epoch=11,train_loss=0.10952389985322952,validate_loss=0.1425563246011734
Train_accuracy=95.49%,validate_accuracy=95.11%
Epoch=12,train_loss=0.10913029313087463,validate_loss=0.14299601316452026
Train_accuracy=95.5%,validate_accuracy=95.07%
Epoch=13,train_loss=0.10873861610889435,validate_loss=0.14222027361392975
Train_accuracy=95.49%,validate_accuracy=95.1%
Epoch=14,train_loss=0.10835383832454681,validate_loss=0.14099833369255066
Train_accuracy=95.5%,validate_accuracy=95.11%
Epoch=15,train_loss=0.10831864178180695,validate_loss=0.14097048342227936
Train_accuracy=95.47%,validate_accuracy=95.12%
Epoch=16,train_loss=0.10763521492481232,validate_loss=0.14083704352378845
Train_accuracy=95.51%,validate_accuracy=95.55%
Current epoch is best so far, saving model...
Epoch=17,train_loss=0.10741936415433884,validate_loss=0.1386122703552246
Train_accuracy=95.5%,validate_accuracy=95.12%
Epoch=18,train_loss=0.10705301910638809,validate_loss=0.13867425918579102
Train_accuracy=95.5%,validate_accuracy=95.12%
Epoch=19,train_loss=0.1068018227815628,validate_loss=0.13918906450271606
Train_accuracy=95.5%,validate_accuracy=95.29%
Epoch=20,train_loss=0.10650665313005447,validate_loss=0.13768768310546875
Train_accuracy=95.51%,validate_accuracy=95.32%
Epoch=21,train_loss=0.10621011257171631,validate_loss=0.1364840269088745
Train_accuracy=95.49%,validate_accuracy=95.64%
Current epoch is best so far, saving model...
Epoch=22,train_loss=0.10582637041807175,validate_loss=0.1353757083415985
Train_accuracy=95.53%,validate_accuracy=95.59%
Epoch=23,train_loss=0.10561032593250275,validate_loss=0.13587422668933868
Train_accuracy=95.5%,validate_accuracy=95.14%
Epoch=24,train_loss=0.10536552220582962,validate_loss=0.13553832471370697
Train_accuracy=95.53%,validate_accuracy=95.34%
Epoch=25,train_loss=0.10524850338697433,validate_loss=0.13436484336853027
Train_accuracy=95.51%,validate_accuracy=95.63%
Epoch=26,train_loss=0.10485772043466568,validate_loss=0.1360331028699875
Train_accuracy=95.54%,validate_accuracy=95.16%
Epoch=27,train_loss=0.10462711751461029,validate_loss=0.13390271365642548
Train_accuracy=95.56%,validate_accuracy=95.17%
Epoch=28,train_loss=0.10459700971841812,validate_loss=0.13329873979091644
Train_accuracy=95.55%,validate_accuracy=95.62%
Epoch=29,train_loss=0.10405617952346802,validate_loss=0.1346481293439865
Train_accuracy=95.57%,validate_accuracy=95.61%
Epoch=30,train_loss=0.10369374603033066,validate_loss=0.1319369524717331
Train_accuracy=95.52%,validate_accuracy=95.61%
Epoch=31,train_loss=0.10324552655220032,validate_loss=0.13234040141105652
Train_accuracy=95.54%,validate_accuracy=95.1%
Epoch=32,train_loss=0.10322153568267822,validate_loss=0.13250146806240082
```

```
Train_accuracy=95.51%,validate_accuracy=95.11%
Epoch=33,train_loss=0.1028430163860321,validate_loss=0.13149401545524597
Train_accuracy=95.59%,validate_accuracy=95.67%
Current epoch is best so far, saving model...
Epoch=34,train_loss=0.10274627059698105,validate_loss=0.1307443529367447
Train_accuracy=95.63%,validate_accuracy=95.65%
Epoch=35,train_loss=0.10265300422906876,validate_loss=0.1318654865026474
Train_accuracy=95.6%,validate_accuracy=95.2%
Epoch=36,train_loss=0.10249429196119308,validate_loss=0.1313396841287613
Train_accuracy=95.64%,validate_accuracy=95.18%
Epoch=37,train_loss=0.10232320427894592,validate_loss=0.13339021801948547
Train_accuracy=95.6%,validate_accuracy=95.19%
Epoch=38,train_loss=0.10221341252326965,validate_loss=0.1316729635000229
Train_accuracy=95.63%,validate_accuracy=95.2%
Epoch=39,train_loss=0.10215899348258972,validate_loss=0.13110613822937012
Train_accuracy=95.61%,validate_accuracy=95.63%
Epoch=40,train_loss=0.10202493518590927,validate_loss=0.13023661077022552
Train_accuracy=95.62%,validate_accuracy=95.2%
Epoch=41,train_loss=0.10193700343370438,validate_loss=0.13016796112060547
Train_accuracy=95.61%,validate_accuracy=95.67%
Current epoch is best so far, saving model...
Epoch=42,train_loss=0.10189375281333923,validate_loss=0.1320798099040985
Train_accuracy=95.64%,validate_accuracy=95.18%
Epoch=43,train_loss=0.10177745670080185,validate_loss=0.13217760622501373
Train_accuracy=95.64%,validate_accuracy=95.18%
Epoch=44,train_loss=0.10190920531749725,validate_loss=0.12984584271907806
Train_accuracy=95.57%,validate_accuracy=95.68%
Current epoch is best so far, saving model...
Epoch=45,train_loss=0.10162931680679321,validate_loss=0.1301572620868683
Train_accuracy=95.62%,validate_accuracy=95.41%
Epoch=46,train_loss=0.10163964331150055,validate_loss=0.13204777240753174
Train_accuracy=95.59%,validate_accuracy=95.19%
Epoch=47,train_loss=0.1016184464097023,validate_loss=0.12976621091365814
Train_accuracy=95.67%,validate_accuracy=95.67%
Epoch=48,train_loss=0.10148406773805618,validate_loss=0.12812942266464233
Train_accuracy=95.65%,validate_accuracy=95.67%
Epoch=49,train_loss=0.10172934085130692,validate_loss=0.12985621392726898
Train_accuracy=95.62%,validate_accuracy=95.66%
```

Output plots

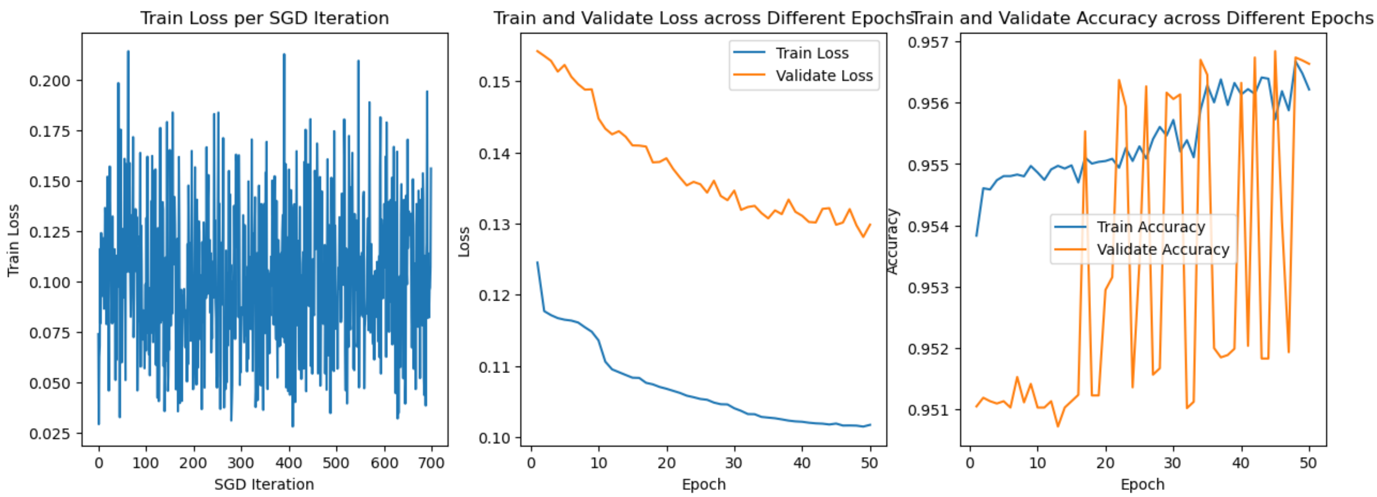
In [138…

```
import matplotlib.pyplot as plt
import numpy as np

# Reshape losses and accuracies arrays to match the total number of train iterations
train_loss_per_iteration = np.array(batch_loss).reshape(-1)

# Create the plots
plt.figure(figsize=(15, 5))

# Plot 1: The train loss per SGD iteration
plt.subplot(1, 3, 1)
plt.plot(train_loss_per_iteration)
plt.xlabel('SGD Iteration')
plt.ylabel('Train Loss')
plt.title('Train Loss per SGD Iteration')

# Plot 2: The train and validate loss across different epochs
plt.subplot(1, 3, 2)
plt.plot(np.arange(1, N_epochs+1), losses, label='Train Loss')
plt.plot(np.arange(1, N_epochs+1), validate_losses, label='Validate Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train and Validate Loss across Different Epochs')
plt.legend()
```

```
# Plot 3: The train and validate metric across different epochs
plt.subplot(1, 3, 3)
plt.plot(np.arange(1, N_epochs+1), accuracies, label='Train Accuracy')
plt.plot(np.arange(1, N_epochs+1), validate_accuracies, label='Validate Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Train and Validate Accuracy across Different Epochs')
plt.legend()

plt.tight_layout
```

Out[138]:

```
<function matplotlib.pyplot.tight_layout(*, pad: 'float' = 1.08, h_pad: 'float | None'
= None, w_pad: 'float | None' = None, rect: 'tuple[float, float, float, float] | None'
= None) -> 'None'>
```



Test Accuracy

In [139…

```
# Load the best model
mybestmodel = myMultilayerPerceptron(x_train.shape[1],7)
mybestmodel.load_state_dict(torch.load("current_best_model"))

test_dataloader = DataLoader(test_dataset, batch_size = batch_size, shuffle = True)
test_batch_accuracy = []

for x_batch, y_batch in test_dataloader:
    prediction_score = mybestmodel(x_batch)
    prediction_label = torch.argmax(prediction_score.detach(),dim=1).numpy()
    test_batch_accuracy.append(np.sum(prediction_label == y_batch.numpy())/x_batch.shape

test_accuracy = np.mean(np.array(test_batch_accuracy))

print(f"Test accuracy = {np.round(test_accuracy*100,2)}%")
```

```
Test accuracy = 95.14%
```

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